[Essays on the antecedents, outcomes and multiplexity of informal innovation networks in an industrial cluster]

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Declaration

In conformance to University regulations, I hereby declare that:

1. This thesis has been composed solely by me;
2. This thesis is entirely my own work; and
3. This thesis has not been submitted in part or whole for any other degree or professional qualification; and
4. The following thesis sections are based on work from jointly-authored working papers:

Thesis Sections	Jointly-authored working papers
Chapter 3: Proximity and its impact on the formation of product and process innovation networks	Golra, O., Rosiello, A & Harrison, R (2019). *Proximity and its impact on the formation of product and process innovation networks.* This paper was presented at *DRUID Academy 2017* in Odense, Denmark; *INFORMS 2017* in Houston, USA; *BAM Doctoral Colloquium* in 2017 at Warwick Business School, UK; *4TH Geography of innovation conference* in 2018 in Barcelona, Spain and *DRUID 2018 in* Copenhagen, Denmark.
Chapter 4: Formation and dynamics of product and process innovation networks: Evidence from a textile cluster in Pakistan	Golra, O., Rosiello, A & Harrison, R (2019). *Formation and dynamics of product and process innovation networks: Evidence from a textile cluster in Pakistan.* This paper was presented at *DRUID 2018* in Copenhagen, Denmark and *Schumpeterian Society Conference (ISS2018)* in Seoul, Korea. It was also accepted for presentation at BAM 2019 at the University of West England, UK.
Chapter 5: Influence of firms' network position on their innovation outcome in a mature industrial cluster	Golra, O., Rosiello, A & Harrison, R (2019). *Influence of firms' network position on their innovation outcome in a mature industrial cluster.* The third paper was presented at *AOM 2019* in Boston, USA and *DRUID 2019* in Copenhagen, Denmark. It was also accepted for presentation at BAM 2019 at the University of West England, UK.

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Abstract

Innovation scholars have been studying social networks for a long time. The two major research concerns have been to understand the origin of social structures and their consequences on innovation. Considerable attention has been given to the analysis of network structures that favour innovation. This stream of research focuses on the structural properties of networks and their effects on innovation. On the flip side, a large number of studies have investigated the underlying mechanisms and driving forces behind these network structures. This stream of research focuses on the individual, dyadic and structural-level drivers of network formation.

Despite these numerous contributions, there are at least three issues in innovation-related network studies that require further investigation. First, multiplexity has received little attention in innovation studies. Notably, scholars have overlooked the formation of multiplex innovation networks. Thus, there is a need to analyse the individual, dyadic and structural level drivers of the formation of multiplex innovation networks. Second, network research is dominated by studies conducted in the western context, and there is a lack of contributions from developing countries. Scholars have also highlighted this issue in recent studies. Third, innovation scholars have mainly focused on undirected networks and formal collaborations, and little attention has been paid to studying directed informal networks. Thus, this thesis aims to fill these research gaps and investigates the antecedents, outcomes and multiplexity of directed and informal innovation networks. The thesis constitutes three papers.

The first paper, “Proximity and its impact on the formation of product and process innovation networks”, contributes to the stream of literature investigating the dyadic-level antecedents of the formation of multiple networks. It analyses the role of multi-dimensional proximity (a dyadic-level driver) in the formation of product and process innovation networks. Using multiple regression quadratic assignment procedure (MRQAP), a social network analysis technique, I study these networks among seventy-three firms in the Lahore textile cluster in Pakistan. I find a significant influence of four

dimensions of proximity on the process of network formation. Notably, the impact of social, cognitive and organisational dimensions of proximity is found to be stronger for process innovation network than for product innovation network. Contrarily, geographic proximity plays a more critical role in network formation for product innovation than process innovation.

The second paper, “Formation and dynamics of product and process innovation networks: evidence from a textile cluster in Pakistan”, also contributes to individual-level and network-level drivers of multiplex network formation. It investigates the influence of individual and relational attributes of actors, as well as endogenous network mechanisms on the formation of product and process innovation networks. Using exponential random graph models (ERGM), this study examines the effect of absorptive capacity and innovative capacity as individual-level attributes; business relations as a dyadic-level factor; and popularity, activity, reciprocity, multi-connectivity and transitivity as network-level characteristics, on the formation of product and process innovation networks. The study finds that individual attributes, relational attributes and endogenous network mechanisms show a significant influence on the formation of both innovations networks.

The third paper, “Influence of a firm’s network position on its innovation outcome in a mature industrial cluster”, employs a social network perspective to investigate the influence of firms’ structural and relational embeddedness on their innovation outcome in a directed network in an industrial cluster. From the structural embeddedness perspective, the paper argues that a central position in an informal advice network does not bring equal innovation benefits to advice-seekers and advice-givers. Notably, in a mature industrial cluster, it is expected that the number of advice giving ties (popularity) positively influences the innovation outcome of firms, whereas the number of advice-seeking ties (activity) negatively affects the firms’ innovation. From the relational embeddedness perspective, the paper investigates the effect of strong and weak ties on the innovation outcome of firms in a mature industrial cluster. It expects a positive relationship between firms’ innovation output and strong ties, and a negative relationship between weak ties and the innovation output of firms. The findings suggest that activity has a significant negative impact on the innovation outcome of firms, while popularity shows a significant positive impact on the innovative outcome of firms. Strong ties show a positive and significant impact on innovation, while weak ties demonstrate a significant adverse effect on innovation. The study also finds that absorptive capacity fully mediates the relationship between advice-giving ties and innovation, and partially mediates the relationship between advice-seeking ties and innovation. This work has implications for cluster policymakers as well as research and development managers.

Lay Summary

A social relation or tie can be defined as any relationship between two or more individuals. A web of social ties among several individuals can be referred to as a network of social relations or a social network. Social networks play an important role in performing crucial activities as they provide access to information and resources. For instance, a friend can provide financial support to the other friend to pay off a bank loan.

Social ties can be distinguished into different types. Kinship, friendship, neighbourhood and work-related ties are some of the common examples of multiple relations among individuals. Moreover, individuals may often be embedded in more than one type of relationship. For instance, two individuals may be friends as well as co-workers, or co-workers can also have kinship relationships with one another. Similarly, neighbours can also be employees in the same organisation, and two business partners can also be spouse partners. A physician can also have a patient-doctor relationship with his/her spouse partner. These examples suggest that ties can emerge either from, inter alia, social, economic, geographical, professional or all of these interactions among individuals.

Moreover, these social interactions can be unidirectional (one way), bidirectional (two way) or asymmetrical. For instance, a knowledge-based relationship between parents and a child is more likely to be a unidirectional relation because the knowledge is transferred from parents to the child. However, a love-based relationship between parents and a child is more likely to be bidirectional. Likewise, a junior manager is more likely to seek work-related advice from a senior manager, whereas a senior manager may not seek work related advice from the junior manager. These examples imply that relationships are not always evenly organised in a social network. Some members tend to have a higher number of contacts than others owing to their status or position in society. Therefore, it is essential to focus on multiple relations in social network studies to have a better understanding of the role of different types of social ties. The present study focuses on multiple relationships among company managers to understand their role in the innovation process of firms. These relationships provide an instant access to knowledge, ideas and resources that may not be easily available to firms through other means.

This study, using evidence from Pakistan, shows how multiple social relations emerge among co-located firms and how these relationships can influence the innovation process of firms. Particularly, it focuses on multiple relationships among firms to study the impact of different factors on the formation of different types of ties. For instance, are closely located two similar technology firms more likely to interact vis-a-vis closely located two firms having a different technological profile? Moreover, this study examines whether a firm with a higher number of ties performs differently than others. It is pertinent to mention here that this study assumes a relationship between two firms when their top managers interact with each other to establish an advice exchange tie. An advice exchange tie occurs when two firms advise each other to solve their innovation-related technical problems. Managerial links represent firms because firms are not living beings and cannot have a friendship or work-related relationship with one another per se.

This thesis consists of three papers which attempts to examine the factors influencing the formation of multiple networks and to investigate the impact of unevenly distributed ties on the innovation performance of firms.

The first paper, “Proximity and its impact on the formation of product and process innovation networks”, contributes to the stream of literature investigating the role of social relations (proximity) in the formation of product and process innovation networks. I find a significant influence of four dimensions of proximity on the process of network formation. Notably, the impact of cognitive and organisational dimensions of proximity is found to be stronger for process innovation network than for product innovation networks. Contrarily, geographic proximity plays a more critical role in network formation for product innovation than process innovation. Social proximity shows similar effect on both innovation networks.

The second paper, “Formation and dynamics of product and process innovation networks: evidence from a textile cluster in Pakistan”, also contributes to individual-level and network-level drivers of multiplex network formation. Results show that individual attributes, relational attributes and endogenous network mechanisms influence the formation of both the product and process innovation networks.

The third paper is “Influence of firm’s network position on their innovation outcome in a mature industrial cluster”. Through the lens of a social network perspective, it investigates the influence of firms’ structural and relational constitution on innovation. Findings suggest that being active decreases the innovation of firms, while being popular enhances the innovativeness of firms. Strong relations show a positive and significant impact on innovation, while weak ties demonstrate a significant adverse effect on innovation. Moreover, the capability to absorb knowledge mediates the relationship between advice-giving ties and innovation.

This study has implications for cluster policymakers as well as research and development managers.

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Chapter 1 Introduction to the thesis

1.1 Introduction

Innovation is the most important engine for the economic growth of firms and regions. However, the prerequisite to produce innovation is the capability to learn and create new knowledge (Boschma, 2005). Knowledge is considered as the most valuable source of innovation and competitive advantage for the firms (Grant 1996). To remain competitive in the market, firms need to regularly update their knowledge stock by combining the existing knowledge with new knowledge (Kogut and Zander, 1992). Firms can create new knowledge through trial, error and experimentation process independently. However, it is nearly impossible to produce all the knowledge components through in-house research and development (Arikan, 2009). Moreover, creating new knowledge through in-house R&D can sometimes be more costly than the benefits it may deliver. Thus, firms may use other mechanisms to acquire new knowledge such as buying licenses, outsourcing research project, and hiring people with needed expertise (Cantner and Graf, 2011; Van Wijk et al. 2008).

In a regional context, one of the most important mechanisms that firms use to acquire external knowledge is through research cooperation with other partners (Cantner and Graf, 2011). Scholars have widely discussed the vital role of joint research and development activities in fostering innovation and knowledge circulation in the regions. For instance, the higher innovative performance of Silicon Valley is often associated with the culture of research cooperation among actors in the region (Saxenian, 1994). Likewise, the presence of informal knowledge linkages among the technical staff and entrepreneurs of co-located firms is another crucial mechanism for knowledge acquisition and diffusion in regions (Almeida, et al. 2011). The successful performance of Third Italy is often associated with the presence of informal contacts between the technicians and entrepreneurs (Becattini, 1990). Over the past decades, scholars have produced ample empirical evidence highlighting the significant role of informal networks in promoting learning and innovation process (Giuliani and Bell, 2005; Boschma and Ter Wal, 2007; Giuliani, 2007; Morrison, 2008). The key argument is that these networks facilitate the circulation of knowledge in industrial clusters (Dahl and Pedersen, 2004; Laursen et al., 2012; Powell and Grodal, 2006) which in turn influence local firms' innovation outcomes (Huber, 2012; von Hippel, 1988).

The importance of networks in innovation has now been widely acknowledged in the literature (Powell et al., 2005). In general, network scholars have addressed two central questions: how social networks emerge and what are the consequences of social structures on these outcomes (Ahuja et al., 2012; Boschma et al., 2014)? Studies focusing on the emergence of networks investigate the underlying mechanisms of the formation, dynamics and evolution of network structures (e.g. Ahuja et al., 2012; Glückler, 2007; Molina-Morales, 2015). These studies show that similarity in individual attributes, relational characteristics and network structural properties facilitate collaboration among actors. While this literature focuses on network formation, the other stream of research pays attention to understanding the impact of network structures on firms' innovation and economic performance (e.g. Ahuja, 2000; Gilsing et al., 2008; Rowley et al., 2000). This literature demonstrates that actors occupying critical positions in the structure of a network perform better than those sitting on less important positions (Batjargal, 2007). The key argument is that prominent positions provide access to diversified information and resources which may not be available through disadvantaged positions in the network (Burt, 2004). Scholars from different fields have significantly contributed to this debate on antecedents and outcomes of networks (Borgatti et al., 2013; Boschma et al., 2014; Cowan et al., 2007; Granovetter, 1985; Powell et al., 2005); however, most of these studies have focused on unitary and undirected networks. Empirical evidence on determinants of multiplex networks (Balland et al., 2016; Brailly, 2016) and the effect of structural embeddedness in asymmetric relations remains scarce (Gargiulo et al., 2009; Tan et al., 2015).

In general, research on topics related to actors' simultaneous embeddedness in multiple types of relationships has received less attention (Lee and Lee, 2015; Shipilov et al., 2014). Studies show that overlapping or multiplex ties improve the frequency of interactions among partners; thus, making the transfer of different types of knowledge more likely (Belso-Martiner et al., 2017; Salavisa et al., 2012). Moreover, multiplexity eases the effective mobilisation of crucial resources as trust between partners is more likely to strengthen due to multiplex ties (Newbert and Tornikoski, 2013). Much research on multiplex networks focuses on the effect of embeddedness in different types of relationships on actors' performance (Shipilov et al., 2014). These studies suggest that actors' embeddedness in multiple relations can significantly influence their performance outcomes (Mazzola et al. 2015, 2016; Ozmel et al., 2013; Ram and Rosenkopf, 2014; Shipilov et al., 2014). For instance, Mazzola et al. (2016) show that an actor's prominent position in interlocking directorate network can improve the flow of information through its inter-firm network which in turn positively influence new product development. Similarly, Ram and Rosenkof (2014) find a significant impact of actors' centrality in commercialisation and knowledge networks on the standardisation process of technologies. While this stream of research provides interesting insight on network multiplexity, scholars argue that most of these studies focus on the impact of multiple relations on the performance of actors and little is known about the antecedents of multiplex networks (Brailly, 2016; Brennecke and Rank, 2017; Shipilov and Li, 2012). Only a few recent studies have attempted to investigate the formation of multiplex networks (Balland et al., 2016; Quatraro and Usai, 2017a). Findings of these studies suggest that different factors facilitate the emergence of multiple types of relations. For instance, Quatraro and Usai (2017a) find significant differences across the formation of citation links, co-inventorships and applicant-inventor relationships. Balland et al. (2016) discover different factors facilitating the formation of business and technical networks. The central argument used in these studies is that multiple types of ties differ from each other in various dimensions which in turn influence the tie formation process. These studies call for further research on the determinants of multiplex networks and highlight that the empirical research on multiplex networks largely remains underexplored. In this thesis, I respond to these calls by studying the formation of product and process innovation networks. I focus on product and process innovation networks because the two innovation types differ from each other on various dimensions[1], which are discussed in detail in chapter 3, and hence provides an interesting case of multiplex networks.

In addition to the limited network studies on multiplex networks, network scholars have conducted very limited studies on asymmetric relations. The significance of studying asymmetric relations in directed networks is also highlighted in recent studies (Casanueva et al., 2013). Scholars pointed out that directed ties are seldom symmetric and it is very unlikely that all members of a network reciprocate ties to one another (Hansen and Mattes, 2018). However, the phenomena of asymmetric relationship has received little attention from scholars (Soltis et al., 2015). Therefore, it is crucial to investigate the impact of actors’ structural embeddedness in a network of asymmetric relations because an imbalance across incoming and outgoing ties can affect the flow of resources and information, which in turn can influence the performance of actors (Gargiulo et al., 2009; Hansen, 2002; Tan et al., 2015).

Therefore, this thesis aims to fill these research gaps by investigating the antecedents of multiplex networks as well as the outcome of actor’s embeddedness in asymmetric relations. In doing so, it brings together the literature from fields of geography of innovation, proximity dynamics, innovation networks and multiplexity to understand the role of firm-level, dyadic-level and structural level characteristics on network formation. This thesis enhances our understanding on distinct impact of proximity dimensions and firm-level characteristics on the formation of product and process innovation networks owing to distinct characteristics of the two innovation types, hence providing an interesting case of multiplex networks. Moreover, the thesis aspires to understand the role of structural and relational embeddedness of firms in asymmetric relations and their impact on firms’ innovation outcome. The ultimate objective of the thesis is to build upon

[1] For detail discussion on the difference among the knowledge characteristics of product and process innovations, please see section 3.2.3 and table 3-2 of this thesis.

established concepts from the literature on innovation and networks to investigate questions related to the role of asymmetric and multiple relations in the innovation process of firms. The following section presents the research motivations of this study.

1.2 Research motivations

The overall research was stimulated by theoretical, practical and personal motivations. Theoretically, the focus of this thesis on multiple networks was motivated given the nascent stage of innovation literature on multiplex and asymmetric ties. In particular, this research is a direct result of the recent calls from innovation scholars to investigate the firm-level, dyadic-level and structural-level determinants of different types of innovation networks (Boschma et al., 2015). Such research is required in order to enhance our understanding about the underlying mechanisms of the formation of multiple innovation networks and their subsequent impact on the performance of actors. Moreover, studying such networks is essential for developing a richer theoretical and practical understanding of the innovation process (Rank et al. 2010). An interesting avenue for research on multiple networks is to focusing on idiosyncratic types of knowledge and innovation linkages. It may be crucial to investigate these linkages because research shows that distinct types of knowledge may require different forms of knowledge transfer mechanisms (Szulanski, 1996). For instance, it is widely acknowledged that codified knowledge can easily be transferred in written forms through templates and manuals, whereas the transfer of tacit knowledge requires face-to-face interaction among actors (Dhanaraj et al., 2004). Since geographic proximity facilitates face-to-face interactions, I can argue that geographic proximity may be more important in facilitating the collaboration when the knowledge to be transferred is tacit than when it is codified. Therefore, it is interesting to examine whether and how does the type of knowledge influence the interaction process among actors. More precisely, whether and how do antecedents of multiple networks differ or relate to one another when ties are composed of distinct knowledge types. In this vein, some scholars suggest investigating the role of geography in the transfer of distinct types of knowledge and resources (Ferru and Rallet, 2016), or investigating the role of geography in facilitating the formation of multiple types of knowledge networks. Therefore, I maintain that it is worth examining the formation of distinct types of innovation-related linkages among actors to enhance our understanding about the role of multiple network in innovation process. In this study, I aim to study the formation of product and process innovation networks. I focus on these two networks because the two innovation types differ in their knowledge characteristics (Gopalakrishnan et al., 1999; Un and Asakawa, 2015). Owing to this difference in knowledge characteristics of the two innovation types, their network formation may also differ. Hence, I stress that it is essential to examine whether determinants of product innovation network differ from process innovation network. Understanding this distinct relationship between product and process innovation networks may contribute to a better understanding of network dynamics and multiple networks, and also opens more avenue for further research in the field of innovation networks.

In addition to above, this research is inspired by recent studies conducted by network scholars who have shown that actors' structural embeddedness in asymmetric relations significantly influence their performance. So far network scholars have mainly focused on undirected networks and, therefore, overlook the role of structural embeddedness in asymmetric relations. It is important to understand the role of structural embeddedness in asymmetric relations because it can impact the performance of actors in different ways. For instance, an actor may be centrally embedded in inward relations and the same actor may be disconnected in outward ties, and vice versa. However, it is not clear whether and how does such structural embeddedness impact the innovation performance of an actor? Therefore, in this study, I aim to investigate the impact of structural embeddedness in asymmetric relations on the innovation performance. This research is theoretically crucial because relations are often asymmetric (Hansen and Mattes, 2018) and till date little is known about the role of asymmetric relations on innovation.

Pragmatically, the motivation of this research was to inform practitioners, such as R&D managers, about the role of asymmetric relations and multiple networks in the innovation process. It is essential to provide insight into the formation and dynamics of multiple relational networks to ensure that R&D managers not only understand the underlying forces behind network formation, but also realise that they are often embedded in multiple types of relationships. Therefore, in order to develop a successful innovation process, managers have to develop effective collaboration strategies to deal with asymmetry and multiplexity of relationships. This research can help managers understand the challenges of collaborating with multiple external partners for exchanging distinct types of resources and knowledge simultaneously, which may help them manage the flow of resources in an innovation process in a more effective manner.

This research was also a results of personal motivations. The researcher's general interest in studying innovation-related topics was nurtured throughout his career. In the past, the researcher has worked in the textile industry of Pakistan as a professional engineer, where he was responsible for managing and improving the quality of textile products and production processes. During his industrial job, he realised that informal social relations among textile engineers play a crucial role in the innovation process as they facilitate the exchange of ideas and resources. Since problems of distinct nature may arise during the development of new products or new processes, the researcher observed that R&D managers often sought advice from variety of colleagues based in different organisations. Moreover, he noticed that problems associated with product development were consulted with variety of colleagues based in other firms, while problems related to production operations were discussed with colleagues working in firms with similar technological profiles.

In addition to the above, there were several other production and innovation-related problems that the researcher observed during his industrial job; however, the time constraint owing to job duties did not allow the researcher to study and understand those interesting research problems. Therefore, the researcher left the industrial job and moved to academia so that he can investigate such innovation-related problems in the industry, which also became an important motivating factor behind this thesis. Moreover, the recently growing literature on multiple networks has also motivated the researcher to investigate the original research problem he observed during his industrial job, that is, why R&D managers consult with distinct types of colleagues to seek advice on product and process innovations?

1.3 Framing research perspectives

1.3.1 Underlying mechanisms of network formation (Paper 1 & 2)

A large number of studies has investigated the underlying mechanisms and driving forces behind the formation and dynamics of network structures. This stream of research focuses on the individual, dyadic and structural-level drivers of network formation (Ahuja et al., 2012; Balland et al. 2013; Balland et al. 2015; Boschma et al. 2014; Giuliani, 2013; Glückler, 2007; Grabher et al. 2018; Huber, 2012; Ozman, 2017; Tasselli et al., 2015; Tsai, 2000; Van Wijk et al., 2008). Moreover, this literature suggests that antecedents and drivers of networks operate at three different levels: structural-level, individual-level and dyadic-level (Boschma et al., 2014). At the structural level, it is argued that network structural properties (e.g. degree centrality, reciprocity, transitivity) shape the evolution of networks (Glückler, 2007; Ozman, 2017). At the individual level, it is maintained that attributes of actors (e.g. absorptive capacity, size) promote collaborations among partners (Cohen and Levinthal, 1990; Giuliani and Bell, 2005; Tasselli et al., 2015). At the dyadic-level, it is suggested that socio-spatial mechanisms (e.g. homophily or proximity relations) facilitate interactive learning and linkage formation among actors (e.g., Grabher et al. 2018; Grillitsch and Rekers, 2016; Huber, 2012; Torre and Rallet, 2005).

More recently, studies on networks suggests that actors are simultaneously embedded in different types of relationships (Shipilov, 2012; Shipilov et al., 2014). These studies find that antecedents of multiple types of networks differ from one another (e.g. Balland et al., 2016; Lee and Lee, 2015; Leenders and Dolfsma, 2016; Leszczyńska & Khachlouf, 2018; Quatraro et al., 2017a). For instance, Balland et al. (2016) study determinants of business and technical knowledge networks. They show that social embeddedness is crucial for the formation of business network while proximity play a vital role in facilitating technical linkage formation. These scholars argue that the main reason for this distinctive relationship is due to the difference in the knowledge characteristics of the two networks. Similarly, Quatraro and Usai (2017a) finds difference across the formation of citation linkages, applicant-inventor relationships and co-inventorship.

In this thesis, I build on these studies and examine the networks of product and process innovations as multiple networks among manufacturing firms in a textile cluster. I am interested in investigating the impact of individual, dyadic and structural level variables on the formation of product and process innovation networks. I have chosen these two innovation networks because these two innovation types play a crucial role in the competitiveness of both the local firms and the industrial cluster (Carbonara, 2017, Un and Asakawa, 2015). Moreover, in this study, I define product innovations as development of new products and services to fulfil customers' and market needs, and process innovations as the new elements that can be new methods, techniques and machines introduced in the firm's production or operations (Casanueva et al., 2013; Damanpour and Gopalakrishnan, 2001). I argue that, understanding the formation and dynamics of product and process innovations will have useful and practical implications for industrial managers, academics and cluster policymakers.

The first two papers in the thesis (Chapter 3 and Chapter 4) investigates the underlying mechanisms and driving forces behind multiplex networks. While the first paper (Chapter 3) examines the relationship between proximity dimensions, and the formation of product and process innovation networks, the second paper (Chapter 4) investigates the impact of individual attributes of firms and network structural characteristics in the formation of product and process innovation networks. To the best of my knowledge, to date, no single study has explicitly analysed the relationship between multidimensional proximity and different kinds of innovation-related interactions in an emerging country's context. Moreover, the role of firm-level attributes and endogenous network mechanisms as determinants of informal networks in emerging countries setting remains underexplored. Therefore, I believe my study is timely as well as crucial to enhance our understanding of the formation and dynamics of multiple networks. This part of the thesis aims to answer the following research questions:

Q1. How different types of proximity dimensions (geographic, social, organisational and cognitive) shape the formation of product and process innovation networks?

Q2. How individual attributes of firms and structural properties of networks influence the formation of product and process innovation networks.

In addition to the first two papers, the third paper investigates the impact of structural and relational embeddedness on the innovation outcomes of firms in an emerging economy's context. Moreover, the paper analyses the impact on asymmetric relations, which have been overlooked in the prior research.

1.3.2 Consequences of social structures on innovation outcome (Paper 3)

In network research, considerable attention has been given to the analysis of network structures that favour innovation (Powell and Grodal, 2006). This stream of research focuses on the structural properties of networks and their effects on innovation. Much research in this field has focused on the concept of structural and relational embeddedness (Cowan et al., 2007). Scholars argue that the performance of a firm depends on its structural position in the network (Batjargal 2007, Balland et al. 2016). Such that a firm with a prominent position in the network tends to have access to crucial resources and knowledge, which consequently affect its innovation (Ahuja 2000, Burt 2004, Zaheer and Bell 2005, Tan et al. 2015). Network literature has discussed various structural positions that can influence the innovation outcome of firms (Borgatti et al., 2013). The most commonly investigated measures of structural embeddedness are: degree centrality, structural holes and density (Batjargal, 2003). However, there is a considerable research gap in our understanding of the role of structural embeddedness on innovation in asymmetric (directed) networks (Gargiulo et al. 2009). Most of the previous studies have either considered structural embeddedness in undirected (symmetric) networks or they have only considered single directions of ties, i.e. in-degree centrality (e.g. Bell, 2005; Casanueva et al., 2013; Tsai, 2001). I argue that it is crucial to take into account both the direction of ties (in-degree and out-degree centrality) because firms may not hold the same structural position in their advice seeking and advice giving relations, which in turn can distinctively affect their performance.

Moreover, several studies emphasise that, although firm's structural position plays an important role, the strength and quality of its inter-firm relationships also affect the innovation output of the firm (Batjargal 2003, Moran 2005). Scholars have widely discussed the role of strong and weak ties on innovation. On the one hand, scholars argue that strong ties are crucial for innovation and knowledge transfer because they promote trust and control opportunistic behaviour (Coleman, 1988; Hansen, 1999; Uzzi, 1997). On the other hand, they argue that weak ties play a more prominent role because they are source of diversified information and ideas (Granovetter, 1973). Moreover, Reagans and Mcevily (2003) argue that strong ties facilitate the transfer of complex and tacit knowledge, while weak ties are more beneficial for the transfer of simple knowledge. In this study, I investigate the impact of both the strong and weak ties on the innovation outcome of firms but in a different context, i.e. a mature industrial cluster in an emerging country.

In addition to that, I investigate the mediating role of absorptive capacity (Cohen and Levinthal, 1990) between a firm's central position in the network and innovation outcome. Previous research suggests that absorptive capacity positively impact innovation outcome (Lane et al., 2006). Prior research further suggest that absorptive capacity positively moderates the impact of central network position on innovation performance (Tsai, 2001). However, in my study, I argue that the effect of absorptive capacity on a firm's innovation outcome depends on the position of the firm in the asymmetric advice-giving and advice-receiving network. I test several hypotheses in the third paper (chapter 5) to support my claim. In doing so, this paper aims to contribute to network research on structural and relational embeddedness as well as network dynamics. In particular, it contributes to the limited studies on the role of a firm as an absorber or provider of information and knowledge (Gargiulo et al., 2009; Hansen, 2002; Tan et al., 2015), and how this role influences the innovation performance of the firms. This paper (chapter 5) addresses the following questions:

Q3a. Whether and how do firms' embeddedness in an advice-seeking role (being active) and advice-giving role (being popular) impact their innovation outcome in the context of a mature industrial cluster?

Q3b. Does absorptive capacity play a mediating role between firms' central position in advice (seeking/giving) network and their innovation outcome?

1.4 Summary of the three papers

In order to answer the above mentioned research questions, this thesis comprises of three empirical studies. Below, I briefly discuss the summary of the three papers.

1.4.1 Paper 1- Proximity and its impact on the formation of product and process innovation networks

The first empirical chapter (Chapter 3) contributes to the stream of literature investigating the dyadic-level antecedents of the formation of multiple networks. It analyses the role of multi-dimensional proximity (a dyadic-level driver) in the formation of product and process innovation networks. The paper argues that the literature on proximity and innovation networks has paid little attention to understanding the relationship between multidimensional proximity and multiple networks. In particular, empirical evidence on the influence of different proximity relations on different kinds of innovation networks remains scarce.

Thus, the first study examines how different types of proximity dimensions (geographic, social, organisational and cognitive) shape the formation of product and process innovation networks.

Using a social network analysis (SNA) based MRQAP model, this paper studies the relationship between four proximity dimensions and innovation networks of new products and new processes in the Lahore textile cluster in Pakistan. Findings suggest that all proximity dimensions show a significant and positive effect on the formation of both innovation networks. Moreover, the cognitive, social (shared past-experience) and organisational proximity show a relatively higher impact on the formation of process innovations network. Contrarily, the impact of geographic proximity is relatively higher on the formation of product innovations network. Social proximity (same university affiliation) is equally important for both the product and process innovation networks.

The results of this paper contribute to the recent debate on proximity and network research, which suggest that different types of knowledge and innovations may have a distinct relationship with different dimensions of proximity (Boschma et al., 2015; Davids and Frenken, 2018; Leszczyńska & Khachlouf, 2018; Quatraro and Usai, 2017). The main contribution of this work is that since product and process innovations differ in the knowledge characteristics, their relationship with spatial and non-spatial proximity dimensions also differ. This study has implications for R&D managers in the manufacturing firms who are responsible for developing new product and new processes. Based on overall findings, the paper argues that since the knowledge associated with process innovations is relatively more tacit and systemic than product innovations (Gopalakrishnan et al, 1999; Un and Asakawa, 2015; Wong et al., 2008); R&D managers should collaborate with proximate partners to minimise coordination problems and ease the transfer of knowledge.

1.4.2 Paper 2- Formation and dynamics of product and process innovation networks: evidence from a textile cluster in Pakistan

The second paper (Chapter 4) contributes to individual-level and network-level drivers of multiplex network formation. Previous research shows that firm-level characteristics and network-level structural properties are important determinants of the formation and dynamics of networks. However, the role of such attributes and properties in explaining the dynamics of multiple networks has received little attention. This paper fill this research gap and investigate the influence of individual and relational attributes of actors, as well as endogenous network mechanisms on the formation of product and process innovation networks.

Thus, the second study examines how individual attributes of firms and structural properties of networks influence the formation of product and process innovations networks.

Using exponential random graph models (ERGM), the study examines the effect of absorptive capacity and innovative capacity as individual-level attributes; business relations as a dyadic-level factor; and popularity, activity, reciprocity, multi-connectivity and transitivity as network-level characteristics, on the formation of product and process innovation networks. Results show that individual attributes, relational attributes and endogenous network mechanisms show a significant influence on the formation of both innovation networks. While absorptive capacity is crucial for both innovation networks, the impact of absorptive capacity is relatively stronger for a product network than a process network. In contrast, innovative capacity negatively influences the formation of both networks.

This result implies that firms with high innovative capacities are less likely to establish linkages with other clustered firms for innovation-related knowledge exchanges. Findings further suggest that business relations are relatively more important for acquiring product innovation-related knowledge than process innovation-related knowledge. In terms of network structural effects, popularity and activity show a significant impact on process innovations network. Similarly, multi-connectivity and transitivity effects show higher values for process innovation networks than product innovation networks, whereas reciprocal ties are more common in product innovation network than process innovation network.

This paper contributes to recent studies on statistical network analysis by analysing multiple networks and also to the debate on network dynamics by analysing the individual, dyadic and structural level driver of multiplex networks. In doing so, first, this paper contributes to studies on advanced social network modelling (Broekel and Hartog, 2013; Harris 2014; Rank et al., 2010; Robins et al., 2012). Second, it contributes to the emerging studies on the individual, dyadic and structural level antecedents of multiplex networks (Balland et al., 2016; Brailly, 2016; Brennecke and Rank, 2017; Giuliani, 2013).

The findings of this paper suggest that, first of all, the dynamics of the formation of product and process innovation networks are inherently different from each other particularly when it comes to the endogenous network properties. The paper shows a significant and positive association between the variable of absorptive capacity and both networks; however this effect is higher for product innovations network than process innovations network. Moreover, the effect is significant only for incoming ties which implies that higher absorptive capacity firms are less likely to seek advice from other clustered firms both for product and process innovations. This study also finds a significant difference in the role of reciprocity, transitivity and multi-connectivity, which suggest that network structural properties influence the formation of multiple network in a different manner.

1.4.3 Paper 3- Influence of a firm's network position on its innovation outcome in a mature industrial cluster

The third paper (Chapter 5) employs a social network perspective to investigate the influence of firms' structural and relational embeddedness on their innovation outcome in a directed network in a mature industrial cluster. From the structural embeddedness perspective, the paper argues that a central position in an informal advice network does not bring equal innovation benefits to advice- seekers and advice-givers. Notably, in a mature cluster, the expectation is that the number of advice giving ties (popularity) positively influences the innovation outcome of firms, whereas the number of advice-seeking ties (activity) negatively affects the firms' innovation. Another expectation is that the access to structural holes has a negative and significant impact on innovation outcomes in a mature industrial cluster. From the relational embeddedness perspective, the paper investigates the effect of strong and weak ties on the innovation outcome of firms in a mature industrial cluster. The paper expects a positive relationship between firms' innovation output and strong ties, and a negative relationship between weak ties and the innovation output of firms.

The third study seeks to answer, whether and how do firms' embeddedness in an advice-seeking role (being active) and advice-giving role (being popular) impact their innovation outcome in a mature industrial cluster?

The paper finds that activity has a significant negative impact on the innovation outcomes of firms, while popularity shows a significant positive impact on the innovative outcomes of firms. Strong ties show a positive and significant impact on innovation, while weak ties demonstrate a significant adverse effect on innovation. This study also tests the mediating effect of absorptive capacity on the relationship between advice ties and innovation. Findings suggest that absorptive capacity fully mediates the relationship between advice-giving ties and innovation, and partially mediates the role of advice-seeking and innovation.

The findings of this study contribute to the debate on the consequences of structural and relational embeddedness on innovation outcomes (Gargiulo et al., 2009; Tan et al., 2015). First, it shows that the impact of a central position in an advice network depends on whether the firm acts as an advice seeker or an advice giver. This paper demonstrates that seeking advice from many other partners in a mature industrial cluster is detrimental for innovation outcomes while receiving advice requests from several other firms increases a firm's innovation outcome. I argue that these findings may be explained by considering the context of the study. Since this study is conducted in a mature industrial cluster where heterogeneity among firms is low (Menzel and Fornahl, 2009), therefore, firms seeking advice from many partners are likely to receive redundant information, which can negatively affect their innovation outcomes owing to the high cost of knowledge search.

This paper also contributes to the literature which analyses the moderating/mediating role of absorptive capacity between a firm's structural embeddedness and its innovation performance (Boari et al., 2017; Shipilov, 2009). This line of research highlights the important role of firms' capabilities as a moderator between different structural positions (e.g. structural holes and brokerage) and innovation outcome. The results of this study show that absorptive capacity plays a role of mediator between centrality and innovation, which suggest that central position is not the actual cause of being innovative instead it is the absorptive capacity that leads to higher innovative performance.

1.5 Thesis structure overview

This thesis comprises of six chapters. The first chapter offered an introduction to the thesis that comprises a portfolio of three research papers. It explains the research motivations behind this thesis and the aims and objectives of this research. Subsequently, second chapter presents the research methodology and offers comprehensive discussion on the designing of this research and the methodological issues related to the research. Next, chapter three, four and five present the three empirical studies undertaken in this research. Finally, chapter six provides a summary of the key findings of the three empirical studies, the overall contributions of the studies, implications of this research, discusses the limitations of this research, and future research directions.

Chapter 2 Methodology

Although each paper in this thesis has a separate research methodology section which explains the data collection and analysis in detail, this section presents the philosophical approach, research strategy, research design and tools of data collection and analysis. It primarily focuses on social network analysis (SNA) tools that are applied for the analysis of social network data. Moreover, in this section, I justify the choice of the SNA tools that I have used in this thesis for the analysis of data.

2.1 Research philosophy

Since there are several branches of philosophy, adopting an adequate philosophical position is essential to any scientific research. Philosophical position is often referred to as 'research paradigm' or 'worldviews'. It is crucial for researchers to understand their philosophical position throughout the research process because their worldviews reflect the way they will conduct the research. Crotty (2003) argue that researchers' understanding of the worldview and their philosophical positions affect the "justification of [their] choice and particular use of methodology" (Crotty, 2003, p2). Therefore, it is necessary to select a research paradigm before starting any research study (Creswell, 2014). Researchers' philosophical underpinnings reflect their beliefs about the nature of reality (ontology) and the process of knowledge creation (epistemology). Ontological assumptions shape how a researcher views the world, and epistemological assumptions shape how a researcher generate knowledge about the world. Huff (2009; p108) defines ontology and epistemology as "ontology considers what exists and epistemology focuses on what human beings can know about what exists". Research paradigms or philosophical assumptions influence the choice of research strategy, design and interpretation of the knowledge.

Traditionally, research on entities, such as firms and organisations, has been dominated by the view that these entities exist independently of the influence of social actors (Gioia and Pitre, 1990). This position represents an objective viewpoint, which investigates organisation-related research problems by applying a deductive approach that tests theoretical predictions through statistical analysis of empirical data (Saunders et al., 2009). In contrast to the objective viewpoint, scholars explore organisational phenomena through subjectivist view, which recognises that “social phenomena are created from the perceptions and consequent actions of those social actors concerned with their existence” (Saunders et al., 2009, p110). In this viewpoint, organisations do not exist independent from the social actors, and indeed, meaning and understanding are subject to interpretations made by researchers (Morgan and Smircich, 1980).

The following section describes the worldview adopted in this research study.

2.1.1 Positivism

The positivist paradigm is positioned within the traditional objectivist natural science philosophy (Saunders et al., 2009). This research study is based on a realist ontological perspective and scientific positivist epistemological perspective, which is methodologically structured by observation-hypothesis-experimentation-verification sequential steps (Kincaid, 1996; Sloane-Seale, 2009). The realist ontological perspective assumes that social reality is objective, and the real world exists independent of labels, i.e. external to the researcher (Huff, 2009). In an epistemological positivist view of the world, scholars can predict and control an objective truth that is out there by searching for patterns and testing hypothesis (Huff, 2009; Sekaran and Bougies, 2013). In this view, scholars start with the observation of already existing theoretical and empirical evidence. Subsequently, they use deductive reasoning to put forward theoretical assumptions (hypothesis), which are aimed to improve knowledge in the specific field of interest (Sekaran and Bougies, 2013). The theoretical predictions are tested through the collection of new empirical evidence which is analysed to verify or falsify the hypotheses formulated. Thus, analysis is predominantly quantitative, where data collection is structured vis-à-vis the predefined research hypothesis. A common critic of positivist paradigm is that it lacks the element of pure discovery in research because it ignores the intricacy of social science studies (Sobh and Perry, 2006).

The two main objectives of this thesis include: investigating the impact of individual-level, dyadic-level and structural-level drivers of network formation; and to examine the impact of structural and relational embeddedness on firms' innovation in a textile cluster in Pakistan. In line with the positivist viewpoint, this research assumes that firms and networks are out there, and they exist independent from the research. Therefore, network formation can be best studied by formulating research hypothesis based on an extensive review of the extant literature and subsequently testing these theoretical predictions through statistical analysis of the empirical data.

2.2 Research strategy

The research strategy assists researchers in establishing a connection between theory and the empirical data. In fact, the research strategy is designed to achieve the main objectives of the research (Saunders et al., 2009). A good strategy helps find appropriate answers to the research questions. The three predominant research strategies are inductive, deductive and abductive (Bell and Bryman, 2018; Creswell, 2013).

The inductive strategy is often associated with exploratory studies, where the particular interest of the researcher is to provide an in-depth understanding of a particular phenomenon in order to develop a theory which is based on the evidence of specific observations (Blaikie, 2010; Trochim and Donnelly, 2006). In particular, inductive reasoning is more appropriate to explore deeply embedded description of a phenomenon rather than to generalise the findings of the study, and hence it is closely affiliated to qualitative data collection methods (Miles et al., 2013).

The second and most commonly adopted research strategy is the natural science-oriented research approach, which follows deductive reasoning. In this approach, a researcher begins by using a general theory about a phenomenon and subsequently deduce hypothesis that describes certain relationships to test whether the theory is able to explain the hypothesised relationships or not. The ultimate aim of the deductive approach is to confirm or refute a theory about the particular observation (Bell and Bryman, 2018; Saunders et al., 2009). In order to test a theory, the researcher proposes causal relationships between different concepts, collects empirical data and uses statistical tools to analyse theoretical predictions (Byrne, 2002). In particular, deductive reasoning is more appropriate for testing theories using large empirical datasets and therefore it is closely associated with the structured quantitative methodology that established credibility and objectivity in order to generalise findings of the study (Saunders et al., 2009).

The third research strategy is the abductive approach, which involves several stages. In this strategy, researchers review existing theories to familiarise themselves prior to empirical data collection. This step of abductive approach is similar to the deductive strategy; however, the researcher does not aim to test hypothesis, instead, he aims to develop a new theory. Therefore, the abductive approach moves on from facts that are deduced from the literature to develop new theoretical explanations of a phenomenon by exploring empirical data. Subsequently, findings are reviewed iteratively with previous theories (Blaikie, 2010).

In this thesis, a deductive research strategy has been adopted. This strategy is appropriate for the research philosophy adopted in this thesis, which is positivism. Bryman (2012: p24) suggests that a positivist perspective require a quantitative deductive research strategy, which offers the process of pursuing the observation-hypothesis-experimentation-verification sequence in the research. Since all the three empirical studies in this thesis adopt positivist research paradigm and postulate several research hypotheses in order to improve existing understanding of the phenomenon of network formation and firm performance. Therefore, a deductive research strategy is applied to test the theoretical predictions to improve the existing theory.

Table 2-1 Summary of adopted research strategy

Research Strategy	Reason
Deductive	➢ Generally, more appropriate for explanatory studies based on positivist research philosophy. ➢ To test the theoretical predictions drawn from the existing literature in order to improve the existing understanding of the phenomenon under investigation and to construct new theory. ➢ To examine relationship between variables through structured data collection and statistical analysis.

2.3 Research design

Due to the nature of this thesis, the research design of this study may not follow standard structure because it comprises three separate yet interrelated studies, which differs from each other in their data analysis approaches. Thus, first, I provide an introduction to overall research design with an emphasis on a cross-sectional design. Subsequently, I discuss the research approach (quantitative), data collection and sampling procedure for the thesis. These sections of the research design are discussed altogether for the overall thesis because the three studies apply the same research approach, data collection and sampling procedure. This is followed by a discussion on the unit of analysis of the three papers. In the end, an overview of the data analysis procedures in the three papers is discussed, followed by a discussion on the pilot study undertaken to improve the research and data collection instruments.

2.3.1 Quantitative research design

The research design provides a framework that assists a researcher in identifying the most appropriate data sources, methods and tools for the collection and analysis of the empirical data in order to find plausible answers to the initial research questions of the study (Saunders, et al., 2009). In other words, a research design is a plan that guides a researcher throughout the process of research. It is crucial to have a comprehensive research design in place prior to commencing any research study because it helps in rationalising the decisions about which dimensions and variables are of interest (Blaikie, 2010; Bell and Bryman, 2018).

In this thesis, I have adopted an explanatory quantitative approach because it is in line with the original philosophy and strategy of my research, which involves objective social reality, positivism and deductive approach. Bryman, (2016: p149) describes quantitative research resign as “entailing the collection of numerical data, a deductive view of the relationship between theory and research, a preference for a natural science approach (and for positivism in particular), and an objectivist conception of social reality”.

Moreover, a quantitative approach is appropriate for network-related studies because researchers have to deal with a large set of relationships among a group of actors. Since my research aims to explain the causal relationship between antecedents of network ties and effects of these ties on firms’ performance, explaining such kind of causal relationship among network ties and other firm-level and dyadic-level variables through qualitative approach may be inappropriate because qualitative approach is applied when the aim is to gather in-depth information rather than to explain causal relationship among variables. Therefore, this study extends the existing theory on network formation among firms through postulating fifteen research hypothesis in the three empirical papers and subsequently testing them through the collection of new empirical data. This procedure is used in order to examine the relationship between dependent and independent variables. In particular, two papers of the thesis postulate ten research hypothesis to examine the impact of different firm-level and network-level variables on the formation of innovation networks. The third paper postulates five research hypothesis to investigate the impact of network structural properties on firms’ innovation outcome. This procedure is widely used by scholars in other social network research of cross-sectional design (e.g. Casciaro, 1998).

2.4 Data collection

After finalising the quantitative cross-sectional research design, an appropriate data collection method should be selected for collecting primary data. This section discusses the empirical plan for this study.

Following the review of literature on antecedents and outcomes of innovation and knowledge networks, as well as firm-level innovation activities, I developed a survey questionnaire to collect information on primary firm-level attribute and network-level relational data. However, researchers interested in network studies must first decide whether they want to study the whole network or the ego network (Marin and Wellman, 2014).

On the one hand, the whole network data approach focuses on all nodes/actors rather than capturing the network surrounding any particular node. In whole network data, a researcher presents each respondent with a list (roster) of actors and asks all of them to indicate the actors with whom they share ties (Hanneman and Riddle, 2014). In this whole network approach, the researcher collects information directly from each network member (Marin and Wellman, 2014).

On the other hand, ego-network data are mostly collected using name generator survey questions. Indeed, it focuses on the network of a particular node (i.e. the ego). In this approach, the researcher does not provide a pre-defined roster; instead, the researcher asks the respondent about his/her relationships with other actors (also known as alters) who share ties (Hanneman and Riddle, 2014). Moreover, in ego-network research, ego provides information about the individual attributes of alters as well as their relationships with others, in contrast to the whole network approach for data collection.

In my research, I focus on large scale active textile firms in the city of Lahore, which are agglomerated in a single cluster, I adopted the whole network data approach instead of ego-network. The list of firms was obtained from the website of APTMA. According to the list, 84 large textile firms are operating in the city of Lahore. During the pilot study, I was told by the managers of pilot firms that some firms had ceased their operations due to the severe energy crisis. Therefore, at the time of data collection, my final list consists of 73 firms in total.

In network studies, once a network approach is chosen, the next step is to choose the method for collecting empirical data. Primary firm-level data can be collected through different methods such as self-administered surveys, telephonic interviews, online surveys and face-to-face interviews (Bell and Bryman, 2018). In this study, I chose an interview-based survey method to collect primary firm-level attribute data as well as network-level relational data. Precisely, I used a semi-structured questionnaire to collect information on firm-level attributes and roster recall-methodology to gather relational data.

I administered the survey through face-to-face interviews and directed them to the head of business units. Borgatti et al. (2013) suggested that in social network research, the researcher should prefer face-to-face interviews for data collection because this process decreases data handling errors and also increases the response rate. Therefore, the data collection was done through face to face semi-structured interviews.

The survey questionnaire sought information on both firm-level characteristics and the advice linkages among firms. There are two sections in the questionnaire[2]. The first section sought information on firm-level attributes such as firm-size, age, innovation and R&D activities, legal status, and exporting and internationalisation activities etc. and managerial-level characteristics such as managers' qualification, experience, employment history, university affiliation etc. Moreover, I gathered information from secondary sources to create further variables such as firms' location, trade memberships and industrial classification etc. These questions help to create both the explanatory and dependent variables for all the three empirical studies in this thesis. Table 2, 3 and 4 provide the definition of all the variables modelled in the three papers respectively, along with the research hypothesis. Moreover, these tables present the measurement methods of all these

[2] The questionnaire is attached as appendix C in the thesis.

variables. The broader network literature has widely used these questions to gather information on firm-level attributes and dyadic-level variables (e.g. Brailly, 2016; Broekel and Boschma, 2012; Giuliani, 2007; Giuliani, 2013).

In section two of the questionnaire, I asked information about the networking activities of firms. Similar questions have been asked by other scholars in network formation studies (Balland et al., 2016; Giuliani and Bell, 2005; Morrison and Rabellotti, 2009; Ter Wal and Boschma, 2007). I asked the following questions from my respondents to map two different networks;

When you need technical advice on product development/innovation, to which of the local firms mentioned in the roster do you turn?

When you need technical advice on process improvement/innovation, to which of the local firms mentioned in the roster do you turn?

In the first and second paper of the thesis, I investigate the relationship between individual-level, dyadic-level and structural-level properties, and the formation of product and process innovation networks. The operationalisation of these variables has been discussed in details in the methodology section of each of the three papers. Please see the methodology section in each paper in the thesis.

Finally, I used interview-based survey method because it allowed me to gather both the quantitative and qualitative information (Sekaran and Bougies, 2013). Quantitative data is often analysed using different descriptive and inferential statistical tools such as regression and factor analysis (Huff, 2009: p184; Saunders et al., 2009). However, I applied network statistical modelling (such as quadratic assignment procedures and exponential random graph models) to examine the phenomenon of network formation in the first two papers in the thesis. In the third paper, a standard ordinary least squares linear regression model was used to explain the relationship among dependent and independent variables.

Table 2-2 Summary of operationalisation of variables in paper 1

Paper 1			
Dependent Variables			
Product Innovation Network	The first dependent variable is a 73*73 socio-matrix for 'product innovations network', which is a dichotomous variable and indicates whether firm 'i' or 'j' mention the other as a source of technological knowledge for new products development		
Process Innovation Network	Similarly, the second dependent variable is a 73*73 socio-matrix for 'process innovations network', which is also a dichotomous variable and indicates whether firm 'i' or 'j' mention the other as a source of technological knowledge for new process development.		
Explanatory Variables	Definition	Research Hypothesis	How it is measured
Geographic Proximity	Closeness in terms of physical distance. (Sometimes other indicators are also used such as co-location of firms.	H1a: Geographic proximity is positively associated with the formation of product and process innovation networks. H1b: The impact of geographical proximity is expected to be higher in the process innovations network than the product innovations network.	Geographic proximity is usually measured as the distance between firms in either physical distance, travel time or simply by co-location (Balland, 2012; Broekel and Boschma, 2012; Molina-Morales et al., 2015). Geographic Proximity$_{ij}$ = 1.82- ln (distance$_{ij}$)
Cognitive Proximity	The similarity in the technological knowledge base of two actors. Two actors have related knowledge bases when they share the same sectoral category or technological class in the industrial classification system.	H2a: Cognitive proximity is positively associated with the formation of both the product and process innovation networks. H2b: The impact of cognitive proximity is expected to be higher on the process innovations network than the product innovations network.	I measure cognitive proximity using cosine similarity index between firms' technology profiles as defined in the Pakistan Standard Industrial Classification (PSIC). Cosine Similarity (A, B) = cos (θ) = $\frac{A \cdot B}{\lVert A \rVert \lVert B \rVert}$
Social Proximity	The existence of familiar relationships or social ties regarding friendship, kinship and same experience between ego and	H3a: Social proximity is positively associated with the formation of both the product and process innovation networks. H3b: The impact of social proximity is expected to be higher on the process	Social proximity is measured in two ways. My first measure is based on university affiliation that is shown to be an important driver of network formation

	alter at the micro level.	innovations network than the product innovations network.	(White, 2011). It is a binary variable, which takes the value '1' if managers/directors of collaborating firms have graduated from the same university, and '0' otherwise. I ask managers about their affiliation with the same university
Organisational Proximity	The similarity in terms of routines and structures between ego and alter; i.e., when they belong to the same parent organisation or the same corporate group.	H4a: Organisational proximity is positively associated with the formation of both the product and process innovation networks. H4b: The impact of organisational proximity is expected to be higher on the process innovations network than the product innovations network.	Organisational takes the value 1 when collaborating firms belong to a single parent organisation or the same industrial group, and 0 otherwise.

Table 2-3 Summary of operationalisation of variables in paper 2

Paper 2			
Dependent Variables			
Product Innovation Network	The first dependent variable is a 73*73 socio-matrix for ‘product innovations network’, which is a dichotomous variable and indicates whether firm ‘i’ or ‘j’ mention the other as a source of technological knowledge for new products development		
Process Innovation Network	Similarly, the second dependent variable is a 73*73 socio-matrix for ‘process innovations network’, which is also a dichotomous variable and indicates whether firm ‘i’ or ‘j’ mention the other as a source of technological knowledge for new process development.		
Explanatory Variables	Definition	Research Hypothesis	How it is measured
Absorptive Capacity	Absorptive capacity is defined as the ability to recognise the value of new information, assimilate it and apply it to commercial ends	H1a. Absorptive capacity is positively associated with the formation of product and process innovation networks; however, this relationship will be positive and significant only when these firms act as advice givers (high in-degree centrality). H1b. The magnitude of absorptive capacity is expected to be relatively higher for the product innovations network than the process innovations network.	A principal component analysis was used to extract a measure of absorptive capacity from three main components, i.e. human capital, research efforts and internationalisation efforts (Please see appendix A for details).
Innovative Capacity	A firm’s ability to exploit knowledge internally	H2. Firms with higher innovative capacity are less likely to establish technical advice linkages with other clustered firms for both product and process innovations.	I measure this by the number of international certifications secured by the local firms such as ISO 9001-2000 quality management system. Cosine Similarity (A, B) = cos (θ) = $\frac{A \bullet B}{\|A\|\|B\|}$
Popularity and Activity	Popularity refers to the attractiveness of central actors and expects that actors with many connections are more likely to establish new	H3a. The popularity effect is positively associated with process innovations network, and there will be no significant association between the popularity effect and the product innovations network.	Measured through counting the in-degree and out-degree of a node.

	connections over time. Similar to popularity effect, the literature highlights the importance of activity effect, which is the tendency of seeking advice from many other actors.	H3b.	The activity effect is positively associated with process innovations network, and there will be no significant association between activity effect and the product innovations network.	
Reciprocity	In this configuration, the presence of a tie between firm i to j encourages firm j to form a reciprocal tie with actor i.	H4.	Reciprocity significantly promotes the formation of product and process innovation networks.	Reciprocity is the number of reciprocal ties of an actor 'i' in the network (Boschma et al. 2015).
Transitivity	This phenomenon is often associated with the cohesion effect, which means that firms tend to connect in stable, closed and dense social structures	H5.	Transitivity significantly promotes the formation of product and process innovation networks. The magnitude of transitivity is likely to be higher for process innovation network.	Transitivity refers to local clustering of actors, and it is measured bu the number of triadic closures in a network.
Business relational network	Number of ties among actors for business related advice	H6.	The business network is positively related with both product and process innovation networks. However, the magnitude will be higher for the product innovations network.	The business network is a dyadic variable measured by the co-memberships of firms in the local trade associations.

Table 2-4 Summary of operationalisation of variables in paper 3

Paper 3			
Dependent Variables			
Innovation	I measure innovation activity by counting the number of international compliance certifications obtained by firms for quality and environment management systems, such as ISO 9001:2015, OEKO-TEX, GOTS, ISO-14001:2015, etc.		
Explanatory Variables	Definition	Research Hypothesis	How it is measured
Strong ties and weak ties	Strong and weak ties are defined as relational embeddedness, which is the strength and quality of the relationship among firms.	H1: Strong ties will positively affect the innovation output of firms H2: Weak ties will negatively affect the innovation outcome of firms	To measure strong ties and weak ties, two additional networks were created. The first network consists of only the overlapping ties (strong-ties network) and the second network consists of all other ties minus overlapping ties (weak-ties network). Network size of each firm was calculated in the strong-ties network to measure strong ties associated with each firm. Similarly, the network size of each firm in the weak-ties network was calculated to measure weak ties.
Advice seeking and advice giving ties	Advice seeking and giving ties are defined in terms of network size (or degree centrality) of firms. Incoming ties are considered as advice-giving ties and out-going ties are considered as advice-seeking.	H3: Advice-giving ties are positively associated with the innovation output of firms in a mature industrial cluster H4: Advice-seeking ties are negatively associated with the innovation output of firms in a mature industrial cluster	Measured by in-degree and out-degree centrality measure, i.e. counting the number of incoming and outgoing ties. Degree centrality, DC (ni) = d(ni)
	Absorptive capacity is defined as the ability to recognise the value of new information, assimilate it and apply it to commercial ends	H5: Absorptive capacity mediates the direct effect of advice-seeking ties on innovation.	A principal component analysis was used to extract a measure of absorptive capacity from three main components, i.e. human capital, research efforts and internationalisation efforts (Please see appendix A for details).

2.4.1 Sample selection

One of the key challenges in network research is the selection of a sample because it is difficult to decide which nodes to include in the study and which to exclude from the study. In this section, I discuss the sample selection and unit of analysis.

In social network studies, researchers can collect and examine data either on an ego network or a complete network (Burt, 1980). The ego network approach focuses on an individual (i.e. ego), alters (i.e. individuals in ego's network) and the interpersonal relationships among them. In contrast, complete network approach requires researchers to identify a list of members and include all of them within the entire network in the sample. In other words, this approach requires a researcher to identify the boundaries of a network in order to collect information on the relationships among all network members (Mitteness, 2009).

Different approaches may be used to identify network boundaries. Three common approaches to specifying network boundaries include a position-based approach, an event-based approach and a relation-based approach (Laumann et al., 1983). The position-based approach considers those actors who hold a specific position or membership in an organisation or a group. The event-based approach considers those actors who participate in particular events, and the relation-based approach considers those actors who participate in social relationships of specified types. These approaches are not mutually exclusive, and researchers can use a combination of more than one method to define network boundaries (Marsden, 2014).

Since my data represents all active large-scale textile firms in the Lahore textile cluster in Pakistan which are registered with All Pakistan Textile Mill Association (APTMA) and Securities and Exchange Commission of Pakistan (SECP), I adopted a combination of a position-based and an event-based to approach to define network boundaries. My network boundary approach is a position-based approach because I only consider those firms that are members of both APTMA and SECP. In other words, a firm meets the position-based boundary criteria, if it holds a position or membership in APTMA and also registered with the SECP. Moreover, the network boundary approach is an event-based approach because I only consider those textile firms from APTMA's list, which are located in the city of Lahore. Laumann et al. (1983) suggest that if two individuals participate in a social event which may be organised in a specific geographical location, then it can be considered as an event-based approach. Since I only selected those firms that are located in the city of Lahore, hence my sampling approach to define network boundaries is an event-based approach. Consequently, in order for a firm to be part of the network boundary, it has to meet both selection criteria.

The reason I adopted these two criteria because, first, there are more than 500 companies that hold membership in APTMA and these companies are located in various cities in Pakistan. Therefore, it may not be possible to gather network related information from all these firms from different parts of the country. Second, there is a large number of small and medium enterprises (SMEs) operating in the city of Lahore, which are neither members of APTMA or registered with SECP. Therefore, it may not be possible to cover all firms in the city of Lahore. So there were 84 firms in total that meet both the network boundary criteria. I prepared the list (roster) of 84 companies to be included in the survey. However, in the pilot study, I learnt that 73 out of 84 companies are actually active in the local cluster, and the remaining companies have become inactive. The geographical representation of active firms is given in figure 2-1 in this chapter.

These firms are large textile firms, and their size ranges from 400 to 7000 employees with a standard deviation of around 1478. Figure 2-2 presents the distribution of a number of employees in each firm. As mentioned elsewhere in this thesis that I have collected information about firms' activities from senior managers responsible for operations management. In some cases, these managers represent large enterprises and therefore may not have information on every aspect of firms. However, the focus of this research is mainly on the technical and innovation-related knowledge exchange and therefore these managers are the most relevant source of technical knowledge. The literature also suggest that knowledge workers (managers) are the main source of knowledge in firms (Huber, 2013). Moreover, the main technical decisions are made at the top managerial level in consultation with mid-level managers. Therefore, it may be reasonable to believe that a top manager of even a very large textile firm is aware of what is going on inside at the operational level. Another reason for choosing top managers to provide information for this research is that they are not only aware of the inside information, but also they are the central point of contact for the external partners. Indeed, I have gathered the information on the number of engineers in each firm to develop absorptive capacity variable. According to the data, on average, each firm employ 22 engineers (managers), which means a top manager may have to coordinate with 22 other managers on an average basis to remain informed about the product/process operational activities.

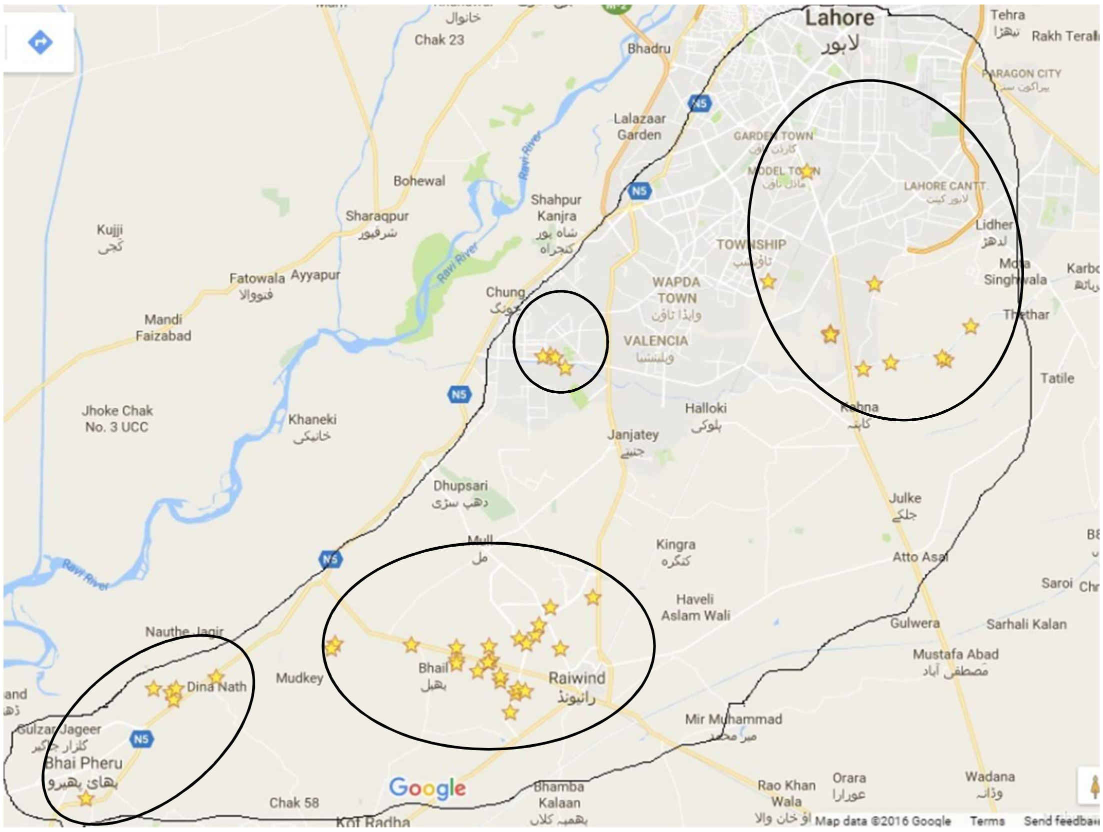

Figure 2-1. Textile firms (stars) shown on the map of the city of Lahore

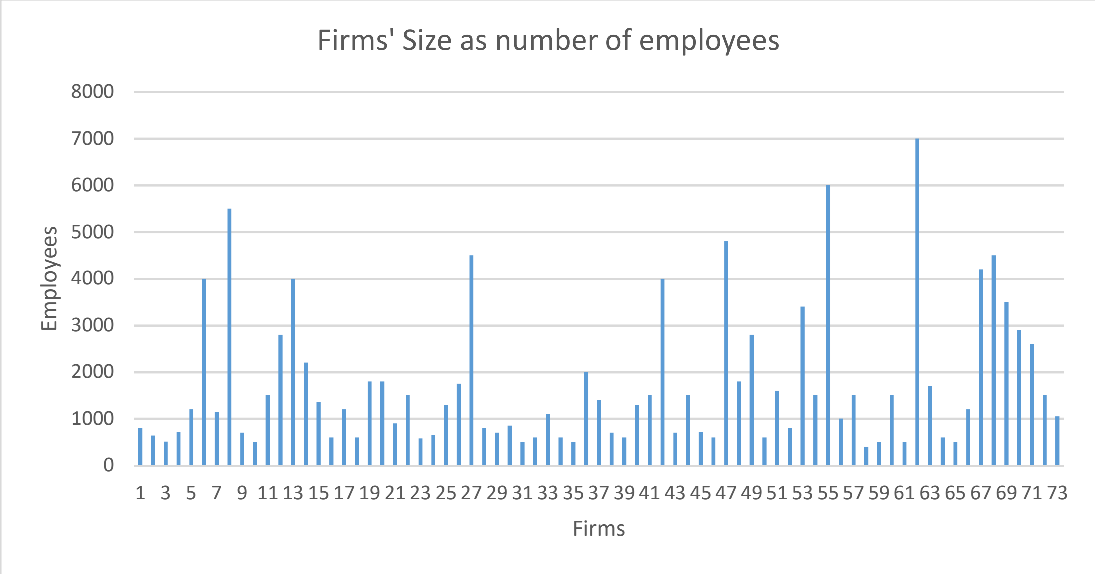

Figure 2-2. Number of employees in each firm

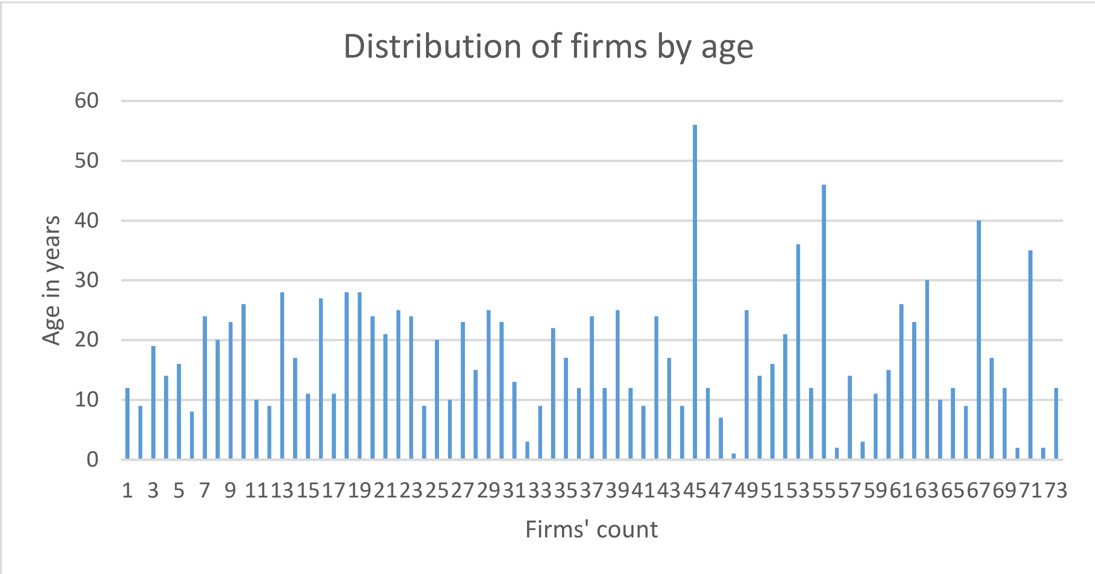

Figure 2-3 Distribution of firms' age

Similarly, these firms also differ in their ages. The youngest firm in my data is as young as two years old, and the oldest firm's age is around 56 years, as shown in figure 2-3. The average age of all firms is around ten years. Moreover, these firms are involved in different technological classes. I followed the Pakistan Industrial Classification System (PICS) codes to distinguish between firm-level technologies. The majority of firms are involved in spinning of yarn technology (26%) followed by textile processing firms (25%), weaving technology (14%), apparel & garments (12%), embroidery work (9%), knitting firms (6%), Home textiles (5%) and knitted apparel (3%). Table 3-3 in chapter 3 present the distribution of firms in each technology. It is pertinent to mention here that many of these firms are involved in more than one technology. A maximum number of technologies per firm is five, and the minimum is one.

In addition to the above, these firms differ in their legal status, exports, R&D and innovation activities. While the majority of firms are public limited firms (50), which are also listed on Pakistan stock exchange, 23 firms are private limited firms. More than half of these firms are significant exporters, which means they export more than 50% of their products. Around 67% of these firms have a separate R&D department for new products and processes development.

While firm-level attributes are important for this study, some managerial level attributes are also important for this research. In particular, this study focuses on informal networks which often represent relationships that exist among employees of different firms. In this regard, it is crucial to gather information on the individual characteristics of the responding person, which in the context of current research is the top manager of each firm. I asked information about the qualification of managers, their university/college affiliation and list of their last three employers. This information helps create explanatory variables. For instance, information on the last three employers and university affiliation help identify shared work/educational experience among managers of different firms, which facilitate collaboration among firms due to social proximity. These variables are discussed in detail in each the methodology sections of the three empirical studies in this thesis.

2.4.2 Unit of Analysis

In the network research, the analysis can be performed at three different levels: the dyad, the node and the network level (Borgatti et al., 2013). In this thesis, the data is analysed at two levels. One is at the dyadic level, and the second is at the firm level. At the dyadic level, I analyse the informal linkage formation among firms. The first and second paper (chapter 3 & 4) focuses on dyadic level analysis. Dyad studies tend to focus on how ties are formed, continued and terminated between a pair of actors (Prell, 2012). The unit of analysis is the links between a pair of actors. It is acknowledged that different factors facilitate the formation of links among actors (Boschma et al., 2014). For instance, the similarity in individual characteristics of firms/individuals can promote interactions among them. Similarly, the similarity in dyadic attributes facilitates collaborations. For instance, co-located firms are more likely to interact with one another as compared to those that are located in different locations. However, incorporating all these different level of analysis in one estimation model to explain a single phenomenon of actor-level interactions may be inappropriate because one may not be able to claim a significant contribution in any specific theory. Therefore, it is best to explain the phenomenon of network formation by incorporating explanatory variables at a single level of analysis or in some cases, perhaps two levels of analysis may be appropriate.

Considering these challenges in mind, in the first paper of this thesis, the level of analysis is purely dyadic, since both the dependent and independent variables are dyadic in this study. The dependent variables are the network matrices of product and process innovations, while the explanatory variables are matrices of proximity dimensions and matrices of control variables. This paper aims to explain the relationship between four proximity dimensions (social, organisational, cognitive and geographic) and their impact on the formation of product and process innovation networks. The idea is that when firms tend to develop a new product or process innovations, they often seek advice from other firms. In this regard, proximity dimensions play a crucial role in facilitating interactions among firms. Scholars in the field of geography have significantly contributed to this literature (e.g. Boschma, 2005). However, limited studies exist on multiple network formation. Therefore, the unit of analysis in this chapter is the relationship among firms.

Similarly, in the second paper (chapter 4), the dependent variables are also dyadic variables, while explanatory variables are both dyadic and firm-level. However, in this paper the explanatory variables are not only dyads (e.g.

business relations) but also individual attributes of actors in the vector format (e.g. firm size, firm's absorptive and innovative capacity) and network-level variables (e.g. reciprocity, transitivity and popularity). Network scholars have shown that similarity in actor attributes facilitate interaction among actors (Robins et al., 2012). Moreover, the current structural position in the network can influence the position of actors in the subsequent period. In line with these studies, the second empirical paper in this thesis examines the formation of linkages among firms for seeking product and process innovation advice. The details of these explanatory variables and other control variables are discussed in chapter 4.

Finally, in the third paper (chapter 5), the level of analysis is at the firm-level. This paper examines the innovative performance of firms based on their network positions. In this paper, the dependent variable in this paper is the innovative outcome of firms; therefore the unit of analysis is firms' innovation performance. Moreover, explanatory variables are the firms' positions in the innovation network (e.g. centrality and structural holes). Borgatti et al. (2013) argue that the structure of any network and the position of firms in that network play a crucial role in predicting the firm-level outcome. The details of the variables are presented in the methodology section of paper 5 in this thesis.

In the subsequent section, I discuss the methods of data analysis.

2.5 Data analysis

Since social network data mainly deal with the analysis of dyads, the standard statistical models are unsuitable for such relationships-based analysis (Marin and Wellman, 2014). Thus, for the analysis of the relational data, the three papers uses three different models: first paper applies multiple regression quadratic assignment procedures (MRQAP) models, the second paper uses exponential random graph models (ERGM), and the third papers uses a mix of SNA tools and standard ordinary least square (OLS) regression. In order to perform social network analysis, a number of software packages have been developed. In this thesis, I predominantly used UCINET 6 (Borgatti et al., 2002) to perform basic social network analysis. Moreover, I used STATNET package in R-software to run MRQAP and ERGM models (Dekker et al., 2007; Snijders et al., 2006). Finally, I used SPSS to perform OLS regression.

In the first paper (chapter 3), I employed multiple regression quadratic assignment procedures (MRQAP), which is more appropriate where the purpose is to investigate the dyadic level driver of network formation. I aim to test the impact of proximity dimensions on the formation of product and process innovation networks. Proximity dimensions are dyadic level variables; thus, I decided to use the MRQAP model. I present a detail discussion in the methodology section of chapter 3 in this thesis.

In the second paper (chapter 4), I employed ERGM. These models are used where the purpose is to examine the role of individual attributes of actors and the structural mechanisms to explain network formation. I aim to investigate the role of a firm's absorptive capacity and network structural effects (e.g. degree, reciprocity & transitivity) on the formation of product and process innovation networks, hence I decided to employ ERGM models. The details about this model are discussed in chapter 4 in this thesis.

In the third paper (chapter 5), I used ordinary least square (OLS) regression analysis to examine the impact of relational and structural embeddedness of firms' on their innovation outcome. I ran different models to test the impact of strong and weak ties on innovation, degree centrality and structural holes, and absorptive capacity to understand the factors responsible for innovation activity in firms.

2.6 Pilot study

I also conducted a pilot study before final data collection exercise. Huff (2009) suggest that researchers should do a pilot or feasibility study during the phase of research design. She identifies several reasons for conducting a pilot study before the final fieldwork (Huff, 2009:p94). Some of the key reasons that are also relevant in my study are as follows;

- ✓ *Developing and testing adequacy of research instruments;*
- ✓ *Establishing whether the sampling frame and techniques are effective;*

- ✓ *Assessing the proposed data analysis techniques to uncover potential problems;*
- ✓ *Collecting preliminary data*

The pilot work was carried out with two main objectives: 1) to test and improve the pilot instrument (questionnaire), which was later used to develop both the dependent and explanatory variables for hypothesis testing, and 2) to verify and update the list (roster) of firms that I obtained from APTMA.

Four firms were visited during the pilot study that were located in the city of Lahore, Pakistan. Two firms were independent units, and both of them were fully equipped with a complete setup of the manufacturing process for their products (which means they do not outsource any of the production processes for their product). The other two firms were part of a group of companies. One of these firms belong to a group that has versatile product ranging from textiles & garments, matrices, cutlery, motorcycles and tractors etc. However, I only visited their apparel manufacturing unit, which was fully equipped with complete manufacturing process equipment. The other firm was part of another group that has multiple units of garment manufacturing and only deals with garments products.

Data was collected through face to face semi-structured interviews. Seven interviews were conducted within four companies to test the pilot instrument. The interviewees/respondents were the senior managers of the firms working in R&D, Product Development (PD), and Production management departments. Before asking the questions, the researcher explained the purpose of the project to the interviewees and then asked their consent for the use of data for research & dissemination.

In the next section, I present a summary of the three papers, which includes the research questions, the methods that I applied and the key findings of the studies.

2.7 Research Setting for this Study

The context of this research is a textile cluster in Lahore, Pakistan. In this section, I will discuss the significance of the context and explains the relevance of the research setting.

The textile industry in Pakistan (TIP) is the oldest and one of the most important industries in the country. It comprises firms operating in all of the production value chain process, i.e. spinning, weaving, processing and garments. The spinning firms produce the yarn from the fibre, weaving firms convert yarn into the fabric, processing firms perform the printing and dyeing functions, and finally garment manufacturing firms prepare the garments and apparels for end users.

TIP plays a vital role in the economic growth of the country because of its significant contribution in the export earnings, domestic industrial production and financial input (Golra, 2016). The industry earns about 54% of the country's foreign exchange. It contributes to 46% of the total manufacturing sector production and also employs about 38% of the local workforce (Pakistan Textile Policy, 2014-19). The industry is dispersed across the country in several clusters. The most prominent textile industrial clusters are located in Lahore, Faisalabad, Sheikhupura, Gujranwala and Rawalpindi in the province of Punjab (Azhar and Adil, 2019); and Karachi, Sukkur and Hyderabad in the Sindh region. Moreover, the country's premier textile industrial association is All Pakistan Textile Mill Association (APTMA), which has 526 registered members all over the country (APTMA, 2014). APTMA members contribute to nearly all of the country's textile exports and 50% of its clothing exports.

In this study, I focus on Lahore textile cluster, which is one of the prominent clusters in Pakistan. Lahore cluster can be characterised as a mature industrial cluster because it has shown sustained growth in the number of textile companies over the last five decades and has also been able to maintain employment on a relatively higher level than several other clusters in the country (Azhar and Adil, 2019; Pakistan Bureau of Statistics, 2013). Menzel and Fornahl (2009, p.218) maintain that "the cluster is able to maintain its employment on a high level in more mature phases". Since the context of this empirical study is a textile cluster based in the city of Lahore-Pakistan, therefore, data is collected from all those APTMA members who have based their operations in Lahore.

Lahore is the second most populous city in Pakistan which is home to around 11.07 Million habitants as per 2018 census (Demographia, 2018). According to a census of manufacturing industries conducted by the Pakistan Bureau of Statistics (PBS) in 2005-06, the city of Lahore accounts for approximately 18% of the total textile and clothing manufacturing firms in the province of Punjab and about 10% in Pakistan (Pakistan Bureau of Statistics, 2013). The census results reported 131 textile and 39 apparel firms from Lahore. These firms are involved in almost all stages of the textile value chain, i.e. yarn manufacturing, knitted and woven fabric manufacturing, dyeing, printing and finishing of fabric, apparel and made-ups manufacturing. Further, they are clustered mainly in four different locations: Raiwind-Manga Road, Ferozepur Road, Bhaiperu-Multan Road, and Defence Road as shown in Figure3-1.

Lahore textile cluster contains some of the most prominent textile firms and/or their subsidiaries in Pakistan. Although, the Lahore textile cluster's knowledge base has been very strong and advanced in spinning, weaving and processing of traditional textile products (Islam, 2006), the potential of apparel and garments manufacturing has only recently been realised in the past couple of years. Several leading firms in spinning and processing of textiles have started investing in apparel and garment manufacturing. However, these firms have been facing competition from countries such as China, India, Bangladesh and Vietnam, because these countries are more experienced in garments and apparel manufacturing.

Moreover, in order to achieve competitiveness in the global market, most of these firms have set-up R&D, product development and design departments locally, as well as in London and Istanbul (Nabi and Hamid, 2013:25-26). Moreover, these firms hire highly paid foreign consultants, mostly from Turkey (because Turkey is relatively advance in denim jeans and apparel washing), to develop new products and processes. The interaction of local workforce with these foreign consultants result in the transfer of innovative knowledge from the consultants to the local workforce. Subsequently, this knowledge spills over to the rest of the firms in the cluster through labour mobility and social interactions among knowledge workers. However, all local firms may not be able to take advantage from these knowledge spill overs because understanding, assimilating and utilising the new knowledge requires a certain level of absorptive capacity (Cohen and Levinthal, 1990). Only those firms that have a minimum level of absorptive capacity may be able to understand and absorb this new knowledge.

Apart from unusual firms-level characteristics, studying the role of proximity in facilitating cooperation among local firms in Pakistan is interesting for several reasons. First, prior research on industrial clusters in Pakistan indicates that, in general, most firms in the country are located in industrial zones (Nadvi and Halder, 2005; Rehman, 2016). Moreover, these studies have shown a positive association between cluster membership, and inter-firm cooperation and innovation, which suggest that geographical proximity is an important factor that facilitates innovative collaboration among local firms.

Second, a strong culture of cooperation and support exist among cluster firms in the Pakistan textile and clothing sector (Islam, 2005). A key reason for this informal culture of collaboration between firms is the strong presence of a community[3] of textile engineers in the local industry who are graduates of the oldest textile institute in the country, the National Textile University, Faisalabad. This university was established in 1959[4], and since then its graduates have been serving the textile industry of Pakistan. NTU offers textile engineering degrees in five disciplines[5] (i.e. spinning, weaving, processing, knitting, garments manufacturing) in line with the industrial requirement. These specialised engineers go into different industrial units related to their

[3] Although there are no formal statistics, it is generally believed that key top-level technical positions in most of the textile firms in Pakistan are held by the graduates of National Textile University, Faisalabad.
[4] History, http://ntu.edu.pk/history.php
[5] BSc Textile Engineering, http://ntu.edu.pk/bste.php (accessed 13-05-2019)

specialised qualifications. The local industry recognises this community of textile engineers as “Textilian”, “BSc’s” or “Manawalian”. Owing to this social and cognitive bonding among managers (Textilians), they tend to support one another on a day to day basis to solve technical problems. This cooperation, in turn, contributes to knowledge circulation in the cluster in a way that the knowledge, which is produced in innovative firms reaches the other local textile firms through informal relations among these managers.

Third, the critical aspect is that a small number of families own several textile firms in Pakistan (Haque, 2007). The embeddedness of firms in entrepreneurial family relations is also an important factor that promotes trust and cooperation among firms in the local cluster (Islam, 2005). This embeddedness nourishes organisational proximity among firms owing to their ownership by a single parent company (family group). Additionally, many of these entrepreneurs are indeed relatives, and hence they advise each other on new investment decisions.

The purpose of discussing the context is to highlight the importance of social relations and their potential role in facilitating collaboration among firms in local clusters. In this context, I have designed this study to investigate the collaboration mechanism between firms in the textile cluster in Lahore. Particularly, to examine the role of dyadic, structural and individual level attributes in shaping the innovation networks. Also to study the effect of structural and relational embeddedness on innovation.

Chapter 3 Proximity and its impact on the formation of product and process innovation networks

3.1 Introduction

Informal (social) networks emerge as a result of social interactions among knowledge workers of different organisations (Gargiulo et al., 2009; Huber, 2012a). These networks play a crucial role in the circulation of knowledge in industrial clusters (Dahl and Pedersen, 2004; Laursen et al., 2012) which in turn influences local firms' innovation outcomes (Huber, 2012a; von Hippel, 1988). An extensive body of knowledge exists on the effects of networks on organisational outcomes (Ahuja et al., 2012), but less attention has been paid to understanding how these networks emerge (Boschma et al., 2014) and what their micro-foundations are (Tasselli et al., 2015). In particular, the antecedents and drivers of multiplex networks remain empirically underexplored (Balland et al., 2016; Lee and Lee, 2015; Shipilov, 2012; Shipilov et al., 2014).

Prior research on unitary[6] relations suggests that antecedents and drivers of networks operate at three different levels: structural-level, individual-level and dyadic-level (Boschma et al., 2014). First of all, at the structural level, it is argued that network structural properties (e.g. core/periphery structure) shape the evolution of networks (Glückler, 2007; Ozman, 2017). Second, at the individual level, it is maintained that attributes of actors (e.g. absorptive capacity) promote collaborations among partners (Cohen and Levinthal, 1990; Giuliani and Bell, 2005; Tasselli et al., 2015). The third driver operates at the dyadic-level and contends that socio-spatial mechanisms (e.g. proximity) facilitate interactive learning and linkage formation among actors (e.g., Grabher et al. 2018; Grillitsch and Rekers, 2016; Huber, 2012a; Torre and Rallet, 2005). These studies predominantly focus on unitary relations and overlook the drivers and antecedents of multiplex relations.

My study stresses the importance of proximity in explaining multiplex network formation because some recent studies have shown that different aspects of proximity distinctively impact multiple types of knowledge interactions (Balland

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[6] Shipilov (2012: 215) defines unitary relations or a unitary network as a type of network in which "organisations are assumed to be monolithic entities that manage a single kind of relationship".

et al. 2016; Davids and Frenken, 2018; Quatraro and Usai, 2017a). For instance, Balland et al. (2016) demonstrate that different aspects of proximity distinctively impact business and technical advice networks. The authors find that while cognitive and geographic proximity plays a significant role in explaining the formation of technical advice networks, their impact on the formation of business advice networks is not significant. Similarly, in a different study, Quatraro and Usai, (2017a) examine the effect of proximity dimension on co-citations, applicant-inventor links and co-inventorships. The authors find a significant difference between the impact of proximity dimensions and the three types of knowledge flows. The authors reveal that technological proximity has a stronger positive effect on citation links, whereas physical contiguity shows the highest impact on co-inventorship collaborations. These studies suggest that it is crucial to investigate the relationship between proximity dimensions and different types of innovation and knowledge for better understanding the proximity and network dynamics.

In this paper, I aim to extend this line of inquiry by examining the relationship between multiple dimensions of proximity and product and process innovation networks. I argue that it is essential to focus on these two innovation types because they play a crucial role in the competitiveness of both the local firms and the industrial district (Carbonara, 2017; Un and Asakawa, 2015). Understanding the proximity dynamics of the product and process innovation networks may help firms better coordinate the knowledge production activities, which in turn may influence firms' competitiveness in clusters. Moreover, prior research on product and process innovations suggests that these two innovation types embody different knowledge characteristics (Gopalakrishnan and Bierly, 2001). While process innovation requires relatively more tacit, unclear, obscure, and systemic knowledge, product innovation requires relatively explicit, clear, concrete, autonomous and simple knowledge (e.g., Casanueva et al. 2013; Gopalakrishnan et al., 1999; Hatch and Mowery, 1998; Krzeminska and Eckert, 2015; Terjesen and Patel, 2017; Un and Asakawa, 2015). Owing to these distinctive knowledge characteristics of the two innovation types, proximity dimensions may play a distinct role in facilitating

R&D collaborations for product and process innovations. Notably, I expect a higher impact of proximity dimensions in the formation of the process network than the product network because the transfer of tacit and systemic knowledge is more complicated than the transfer of explicit and simple knowledge (Van Wijk et al., 2008).

Thus, my contribution lies in the emergent literature on proximity and network dynamics (Balland et al., 2016; Davids and Frenken, 2018; Huber, 2012a; Torre and Wallet, 2014), network multiplexity (Bliemel et al., 2014; Lee and Lee, 2015; Leenders and Dolfsma, 2016; Leszczyńska & Khachlouf, 2018; Mazzola et al., 2016; Ram & Lori, 2014; Shipilov, 2012; Shipilov et al., 2014) and the geography of innovation activities (Balland and Rigby, 2017; Grabher et al. 2018; Grillitsch and Rekers, 2016; Shearmur and Doloreux, 2015; Shearmur et al., 2016). The paper integrates the literature on multidimensional proximity and multiple networks to examine how different types of proximity (geographic, social, organisational and cognitive) shape the formation of product and process innovation networks.

My measure of proximity is primarily based on Boschma's (2005) seminal paper which introduces an analytical framework comprising five critical dimensions of proximity. This framework suggests that the geographic, social, organisational, cognitive and institutional proximity[7] are the main forces behind inter-organisational learning and the innovation process (Boschma, 2005; Knoben and Oerlmans, 2006).

The structure of the paper is as follows: The next section discusses the relationship between network and proximity concepts and explains why proximity might be essential to study the network of product and process innovation; in section three, I present my research hypotheses; the data and methodology are presented in section four; and the results are discussed in

[7] Our paper does not include the institutional dimension because it is not relevant in the context of the present study because our sample of firms only includes the local textile manufacturers from different stages of the textile value chain, and they all work under the umbrella of similar institutional rules. Therefore, institutional proximity is not considered in this paper.

the fifth section. I conclude in the last section with the limitations of the current study and suggestions for future research.

3.2 Literature review

3.2.1 The proximity perspective

Table 3-1 Overview of the dimensions of proximity

Proximity Types	Definition	References
Geographic Proximity	Closeness in terms of physical distance. (Sometimes other indicators are also used such as co-location of firms).	(Aguiléra et al., 2012; Balland et al., 2013; Boschma, 2005; Boschma et al., 2014; Balland et al., 2016; Broekel and Boschma, 2012; Davids and Frenken, 2018; Knoben and Oerlemans, 2006; Molina-Morales et al., 2015).
Cognitive Proximity	The similarity in the technological knowledge base of two actors. Two actors have related knowledge bases when they share the same sectoral category or technological class in the industrial classification system.	
Social Proximity	The existence of familiar relationships or social ties regarding friendship, kinship and same experience between ego and alter at the micro level.	
Organisational Proximity	The similarity in terms of routines and structures between ego and alter; i.e., when they belong to the same parent organisation or the same corporate group.	

The notion of proximity emerged in the 1990s primarily to study the phenomena of the creation, organisation and diffusion of innovation (Bouba-Olga et al., 2015). The concept maintains that proximity between partners' attributes is crucial for the coordination of various activities such as knowledge transfer, strategic information and economic activities (Torre and Wallet, 2014). Over the last decade, scholars have increasingly acknowledged that not only spatial proximity, but also non-spatial proximity influence the learning process between organisational entities (e.g., Agrawal et al., 2008; Hansen and Mattes, 2018; Huber, 2012a). Some scholars argue that geographical proximity is not important in itself, but matters because it enables proximity in other dimensions (Broekel and Boschma, 2012; Fitjar et al. 2016). While the extant literature has discussed various definitions and typologies of proximity (Torre and Gilly, 2000; Knoben and Oerlmans, 2006), analytical distinctions proposed by Boschma (2005) have been widely adopted. Boschma's (2005) seminal paper suggests that geographic, social, organisational, cognitive and institutional proximities are the predominant forces behind the inter-organisational learning and innovation process. Table 3-1 gives an overview of the four proximity dimensions.

Geographic proximity has been the most widely discussed analytical dimension in the extant literature. It is defined as co-location or nearness between partners in terms of territory, space and physical distance (Aguiléra et al., 2012; Knoben and Oerlemans 2006). Geographic proximity facilitates frequent face-to-face interactions among actors which in turn enables trust between them (Moodysson et al., 2008) and also promotes interactive learning and knowledge spillovers (Jaffe et al., 1993; Bell and Zaheer 2007). In addition to geographic proximity, other non-spatial proximity dimensions also play a critical role in interactive learning and innovation (e.g., Fitjar and Rodríguez-Pose, 2015; Hansen and Mattes, 2018; Huber, 2012a; Regional Studies, 2015). Notably, cognitive proximity is essential for R&D and innovation collaborations.

Cognitive proximity refers to the similarity in terms of knowledge or technological bases of actors (Nooteboom, 2000). Cognitively proximate actors perceive, interpret, understand and evaluate the world in a similar manner (Wuyts et al., 2005) owing to the similarity in their knowledge bases (Broekel and Hartog, 2013). The similarity in knowledge bases increases the likelihood of tie formation between actors which in turn may increase the likelihood of information and knowledge exchange (Lazzeretti and Capone, 2016). However, research also shows that too much cognitive proximity is detrimental for learning and innovation because the knowledge bases of actors become so similar that they may not be able to offer any new knowledge to each other which leads to a lock-in situation. Therefore, ego should collaborate with alters having optimal cognitive distance (Nooteboom et al., 2007).

Social proximity refers to the embeddedness of actors in trustful social relations (Granovetter, 1985; Maskell and Malmberg, 1999). It indicates that actors tend to establish connections with other actors with whom they have embedded social relations (e.g., kinship, friendship and family ties) and where a certain degree of trust exists between these actors (Boschma, 2005; Broekel and Hartog, 2013; Lazzeretti and Capone, 2016). Trust facilitates information and knowledge exchange (Von Hippel, 1987) because it avoids opportunistic behaviour (McEvily et al., 2003). Nilsson and Mattes (2015) argue that frequent face-to-face meetings and participation in social events enable deep trust between partners, which in turn play a critical role in the transfer of knowledge among partners (Balland et al., 2016; Broekel and Boschma, 2012; Molina-Morales et al., 2015).

Organisational proximity refers to the similarity in terms of organisational routines and structures among collaborating partners. For instance, there is a clear distinction between the routines and structures of profit and non-profit organisations. Broekel and Boschma (2012) argue that non-profit organisations (e.g. universities) are more open to knowledge sharing with the external partners, whereas profit organisations (e.g. private firms) tend to hide knowledge from competitors. Owing to different routines, profit and non-profit organisations will have low organisational proximity. Organisational proximity is also defined as the degree of strategic interdependence between organisations (Broekel and Hartog, 2013; Lazzeretti and Capone 2016). For instance, two organisations are organisationally proximate if they belong to the same corporate group (Boschma et al., 2014*)*.

3.2.2 Proximity and networks

To date, several empirical studies have applied Boschma’s (2005) analytical framework to explain the inter-organisational learning and innovation process (e.g. Balland 2012; Broekel and Boschma 2012; Geldes et al. 2015; Hansen and Mattes, 2018; Huber, 2012b; Lazzeretti and Capone, 2016). The findings of these studies suggest that both the spatial and non-spatial dimensions of proximity play an essential role in facilitating interactions among actors, which in turn promotes the learning and innovation process (e.g. Regional Studies, 2015). However, some recent empirical studies argue that the relative importance of proximity dimensions depends on the type of knowledge that is being exchanged (Balland et al., 2016; Davids and Frenken, 2018; Quatraro and Usai, 2017a). These studies also reveal that the influence of different dimensions of proximity is distinctive for diverse kinds of networks (e.g. Balland et al., 2016; Brailly, 2016; Quatraro and Usai, 2017a). For instance, Balland et al., (2016) study the impact of various proximity dimensions on the formation of the business and technical advice networks. The authors demonstrate that while cognitive and geographic proximity plays a significant role in explaining the formation of technical advice networks, their impact on the formation of business advice networks is not significant.

In another more recent study, Quatraro and Usai (2017a) investigate the impact of geographic, technological and institutional proximity across diverse kinds of knowledge flows, i.e., citation links, applicant-inventor links and co-inventorships. The authors find significant differences between the impact of proximity dimensions and the three types of knowledge flows. They reveal that technological proximity exerts the highest influence on citation links, whereas physical contiguity shows the highest impact on co-inventorship collaborations. In a similar vein, some scholars distinguish between analytical, synthetic and symbolic knowledge to understand the differentiating impact of proximity dimensions (Davids and Frenken, 2018; Mattes, 2012). For instance, Davids and Frenken (2018) show that while the production of analytical knowledge requires high cognitive proximity between partners, permanent co-location is crucial for the production of synthetic knowledge. In a different context, Leszczyńska and Khachlouf (2018) study the impact of proximity dimensions on horizontal and vertical linkages formation. The authors find that social and cognitive proximity is critical for facilitating horizontal interactions among firms in industrial districts, whereas vertical interactions occur at social and cognitive distances.

These findings suggest that the relative importance of each proximity dimension depends on the characteristics of the relationship that is being analysed and the knowledge that flows through these relationships. Despite these recent studies, the empirical evidence on the relationship between multidimensional proximity and multiplex relations is lacking (Balland et al., 2016; Leszczyńska and Khachlouf 2018). Therefore, to contribute to this recent debate, the present paper analyses four of Boschma's (2005) proximity dimensions (i.e., social, organisational, cognitive and geographical) to explain the interactive learning and innovation process in two different types of innovation networks, i.e. product and process innovation networks. Since my aim in this study is to investigate the impact of different proximity dimensions on the formation of product and process innovation networks, it is crucial to understand the nature and characteristics of these two innovation types. Thus, before presenting my research hypothesis (conceptual framework) in section 2.3, I discuss the relative differences between product and process innovations in the next section, 2.2.3.

3.2.3 Relative differences between product and process innovations

Product innovation is defined as developing new products and services to fulfil customers' needs, while process innovation is defined as new elements introduced in firms' operations (Damanpour and Gopalakrishnan, 2001). Product and process innovations play a crucial role in the competitiveness of both the firms and the industrial district (Carbonara, 2017, Un and Asakawa, 2015). However, developing new products and new processes is a complex process, which requires cooperation and coordination with various external sources and diversified partners (Antonelli and Fassio, 2016). Indeed several studies have provided evidence that the role of external sources for product innovations is different from process innovations (e.g. Gemünden et al., 1996; Freel and Harrison, 2006; Kang and Kang, 2010; Reichstein et al., 2008), which suggest that the choice of a partner depends on the type of innovation. Moreover, prior research on product and process innovations suggests that these two innovation types embody different knowledge characteristics (Gopalakrishnan and Bierly, 2001), which in turn may influence the collaborative activities of firms for each innovation type (e.g. Krzeminska and Eckert, 2015; Un and Asakawa, 2015).

Following recent empirical work on R&D collaborations and types of innovations, this paper subsequently discusses the relative difference between the product and process innovations on six dimensions of analysis in Table 3-2. These analytical dimensions are: the objective of innovation, its competitive impact, its valuation, its degree of novelty, its imitability and its substitutability (Un and Asakawa, 2015).

Table 3-2 Relative differences between product and process innovations

Dimensions of Analysis	Product Innovation	Process Innovation
Objective of innovation	Novelty	Efficiency
Competitive impact	Price, market share	Cost, quality control
Valuation of innovation	External evaluation by customers	Internal evaluation by managers
Degree of novelty	Radical, exploratory learning	Incremental, exploitative learning
Knowledge codification	Clear, concrete, explicit	Unclear, obscure, tacit
Knowledge substitution	Autonomous, separable, simple	Systemic, interdependent, complex

(Source: Un and Asakawa 2015)

The first dimension distinguishes product and process innovations by the underlying objective of the innovation. The objective of process innovation is to improve firms' productivity and efficiency (Wong et al., 2008; Terjesen and Patel, 2017). Firms can improve the yield and efficiency of the process by harmonising the development and manufacturing facilities (Hatch and Mowery, 1998). In contrast, the purpose of product innovation is to achieve product novelty (Un and Asakawa, 2015), which enables firms to differentiate their offers from those of their competitors. Interaction with diverse knowledge sources can play a crucial role in developing innovative products (Fitjar and Rodríguez-Pose, 2011). Second, product and process innovations can be distinguished by their competitive impact. In the case of process innovations, the competitive impact is a reduction in the manufacturing cost of the existing products or services (Reichstein and Salter, 2006).

In addition to the reduction in the cost of products, process innovations improve product features and their quality. Contrarily, the competitive impact of product innovation is an increase in the price that the firm can charge from its customers for providing additional features in the new product (Un and Asakawa, 2015). Moreover, a firm may be interested in increasing its market share. Therefore, it may focus on product innovation (Damanpour and Gopalakrishnan, 2001).

The third dimension is the valuation of innovation. Process innovations are valued internally by the firm’s managers (Utterback and Abernathy, 1975), who set various improvement targets and cost reduction goals for the production process (Un and Asakawa, 2015). In contrast, product innovation is more observable and valued externally by customers (Damanpour, 2010). Customers or end users evaluate the performance of products in comparison to the products offered by competitors.

The fourth dimension is the degree of novelty. Product innovation tends to focus on the exploratory learning process to achieve radical improvement. Diversity in sources of knowledge and ideas is critical for the development of radical product innovation (Fitjar and Rodríguez-Pose, 2011). On the contrary, process innovations tend to focus on incremental innovations through an exploitative learning process. The focus in process innovations is on the improvement of existing concepts and ways of doing things (Un and Asakawa, 2015; Westerlund and Rajala, 2010).

The fifth dimension entails the codifiability of knowledge. Process innovation is less clear, less visible and more obscure than product innovations (Un and Asakawa, 2015). Moreover, process innovations tend to be more tacit because they are internally embedded in different parts of the organisation (Gopalakrishnan et al., 1999), which makes them more difficult to codify (Hatch and Mowery, 1998; Wong et al., 2008). In contrast, product innovation is relatively more explicit, clear, and concrete in nature than process innovations (Krzeminska and Eckert, 2015; Terjesen and Patel, 2017). The knowledge is embodied in the product, which is introduced as output for customers (Utterback and Abernathy, 1975); thus competitors may be able to get the product from the market and imitate it via reverse engineering (Un and Asakawa, 2015).

The sixth dimension involves the location of the knowledge for innovation. Process innovations are systemic and interdependent (Gopalakrishnan et al., 1999; Terjesen & Patel, 2017; Un and Asakawa, 2015; Wong et al., 2008). Moreover, process innovations are relatively more complicated than product innovations because they are more interrelated with other systems of the organisation (Gopalakrishnan et al., 1999), in turn making them more context-specific in nature, as well as making it harder to understand how and why the process works because of causal ambiguity among different parts of the system (Un and Asakawa, 2015). By contrast, product innovation is separable and autonomous since it is developed and implemented separately from other systems of the organisation in a quasi-independent unit such as a dedicated R&D department (Un and Asakawa, 2015). Moreover, product innovation is relatively simple and easy to understand because it is more observable (Gopalakrishnan et al., 1999). Thus, it may be relatively easy to substitute. The next section presents the research hypothesis of the study.

3.3 Research Hypotheses

3.3.1 Proximity as a determinant of product and process innovation networks

Recent studies suggest that the impact of proximity dimensions differ across the type of knowledge flows (Balland et al., 2016; Quatraro and Usai, 2017a). For instance, Davids and Frenken (2018) show that synthetic, symbolic and analytical knowledge generally require different types of proximity for mobilisation. Similarly, Quatraro and Usai (2017a) observe that depending on the tacit and codified content of knowledge flows, proximity dimensions can play a distinct role in linkage formation. Building on these studies, I maintain that proximity dimensions may have a different impact on the creation of product and process innovation networks because the knowledge characteristics of product innovations differ from those of process innovations. I also expect that while spatial and non-spatial proximity dimensions are essential for both innovation networks, this impact may be relatively higher in the process innovations network than the product innovations network.

The fundamental tenet is that the knowledge associated with process innovation is tacit, obscure, interdependent and systemic, whereas the knowledge related to product innovation is explicit, clear, concrete, codified and autonomous (Gopalakrishnan et al., 1999; Casanueva et al., 2013; Hatch and Mowery, 1998; Krzeminska and Eckert, 2015; Terjesen and Patel, 2017; Wong et al., 2008). The tacit, systemic and idiosyncratic nature of process knowledge make it context-specific, which resides in the skills of individuals and the routines of firms (Nelson and Winter, 1982). This characteristic of knowledge limits the potential for spillovers (Breschi and Malerba, 1997), which in turn makes knowledge transfer difficult across organisations (Un and Asakawa, 2015). Moreover, understanding the exact element of systemic and tacit knowledge package, and replicating it to a different user setting is very difficult (Spender and Grant, 1996). Indeed, the higher the causal ambiguity and systemic interdependence of knowledge, the less easily the knowledge can be substituted and transferred (Un and Asakawa, 2015).

Research suggests that the importance of spatial and non-spatial proximity in future cooperation increases with an increase in the tacitness and complexity of knowledge (Van Wijk and Jansen, 2008). The smooth transfer of tacit and idiosyncratic knowledge requires a higher level of coordination between firms, which in turn requires high proximity among partners in both the spatial and non-spatial dimensions (Aguiléra et al., 2012). Therefore, the likelihood of firms being linked to proximate partners may be higher when the knowledge to be transferred is tacit and obscure.

In contrast, the simple, explicit and codified knowledge can easily be transferred in the form of templates, manuals and through other written methods; thus, it does not require a high level of coordination, trust and socialisation among partners for its transfer (Dhanaraj et al., 2004). Therefore, interactions among less proximate partners in geographic and non-geographic dimensions may be sufficient for the exchange of explicit and codified knowledge. This suggests that the likelihood of collaboration between proximate actors may be lower for explicit and codified knowledge.

In addition to tacitness and complexity of knowledge, product and process innovations differ in their learning strategies. Process innovations tend to focus more on the exploitative learning process to achieve higher production efficiencies in operations by introducing incremental innovations (Menzel et al., 2017), whereas product innovations tend to focus more on the exploratory learning process to attain novelty via introducing radical innovations (Un and Asakawa, 2015). The idiosyncrasy in the learning strategies and objectives can also impact the way firms form ties with their partners (Menzel et al., 2017). For instance, Westerlund and Rajala (2010) reveal in their study that when the learning orientation of firms is explorative, they tend to collaborate with new partners for both product and process innovations. By contrast, when the learning orientation is exploitative, firms closely work with established partners to develop process innovations only.

In sum, I argue that, although all proximity dimensions are important for both product and process innovation networks, they may be more crucial for the latter than the former. This is because process knowledge is more systemic and tacit than product knowledge (Gopapakrishnan et al. 1999; Wong et al., 2008). In other words, the likelihood that a firm will successfully establish a knowledge linkage with other firms depends on two key factors. First, it depends on the type of knowledge that is being exchanged and, second, on the proximity between the collaborating partners. The more systemic and tacit the knowledge (as in the case of process knowledge), the higher the likelihood that the knowledge linkage will be established between more proximate partners and vice versa. This paper now presents the research hypothesis in the next section on how geographic, cognitive, social, and organisational proximity dimensions respectively influence the network formation of product and process innovations.

Figure 3-1 presents the pictorial representation of my conceptual framework that demonstrates the relationship between four proximity dimensions and the innovation networks of new products and new processes.

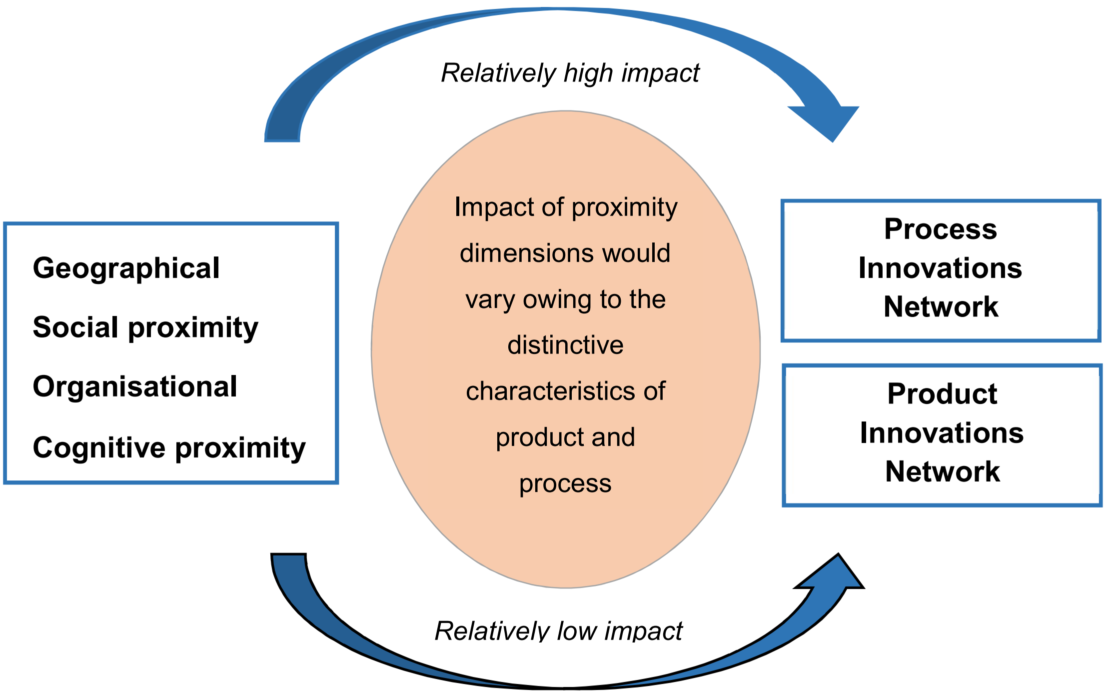

Figure 3-1 Impact of proximity dimensions on the formation of product and process innovations

3.3.1.1 Geographic proximity as a determinant of product and process innovation networks

Geographic proximity refers to nearness between partners in terms of territory, space and physical distance (Aguiléra et al., 2012; Knoben and Oerlemans 2006). The current paper proposes that geographical proximity may positively impact the formation of both the product and process innovation networks. Nevertheless, I expect that this impact may be higher for the process innovations network than the product innovations network.

The literature suggests that the transfer of tacit knowledge requires a certain amount of face-to-face interactions, which are facilitated by geographical proximity (Aguiléra et al., 2012; Boschma, 2005). Geographic proximity may directly influence the likelihood that two actors will engage in knowledge exchange (Broekel and Boschma, 2012). Therefore, firms that require advice on tacit knowledge may prefer to interact with geographically proximate partners. Whittington et al. (2009) aver that tacit knowledge is less easily transferred between distant partners. Thus, lowering the distance between partners can make the transfer of tacit knowledge more easy (Von Hippel, 1998; Maskell and Malmberg, 1999). Indeed, geographical proximity can play a predominant role in the co-development and transfer of tacit and sticky knowledge by facilitating interactions (Asheim et al., 2007; Bathelt et al., 2004).

Moreover, Balland and Rigby (2017) have shown that while the likelihood of the diffusion of complex knowledge increases with the decrease in geographic distance between partners, the increase in geographic distance between partners decreases the diffusion of complex knowledge. Their research further suggests that simple knowledge can be diffused easily at both shorter and longer geographic distance, whereas complex knowledge is difficult to diffuse at a longer distance. Similarly, Dhanaraj et al. (2004) demonstrate that simple and codified knowledge can be transferred between geographically distant partners. However, Boschma (2005) argues that although simple and codified knowledge is less space-sensitive, it may still require some level of geographical proximity. Thus, I submit the following hypotheses:

H1a: Geographic proximity is positively associated with the formation of product and process innovation networks.

H1b: The impact of geographical proximity is expected to be higher in the process innovations network than the product innovations network.

3.3.1.2 Cognitive proximity as a determinant of product and process innovation networks

Cognitive proximity refers to the similarity in terms of knowledge or technological bases of actors (Nooteboom, 2000). Since the knowledge characteristics of product and process innovations are fundamentally different, the role of cognitive proximity is expected to have a different impact on the network formation of the two innovation types. In this study, I expect that cognitive proximity plays a positive and significant role in the formation of both the product and process innovation networks. This impact is expected to be higher for the latter than the former.

Cognitive proximity is important for the inter-firm network formation because the similarity in the knowledge base and shared skills is critical in understanding the knowledge of partners properly (Boschma, 2005). Moodysson et al. (2008) argue that cognitive proximity is more important than geographic proximity for interactive learning. Mattes (2012) asserts that cognitive proximity is always important and that it is crucial in any type of knowledge exchange, i.e. synthetic, symbolic and analytical knowledge. Balland and Rigby (2017) argue that complex knowledge is more valuable and more difficult to produce than simple knowledge, and its diffusion becomes even more complicated when the knowledge bases of the two collaborating partners are cognitively distant. Therefore, cognitive proximity between partners may be more important in the diffusion of complex and systemic knowledge.

Moreover, the transfer of tacit and idiosyncratic knowledge requires a high level of coordination between partners (Aguiléra et al., 2012) and cognitive proximity facilitates effective communication and coordination (Boschma, 2005), which in turn eases the transfer of the tacit knowledge (Wuyts et al., 2005). Balland et al. (2016) show that cognitive proximity plays a more important role in the transfer of technical knowledge than the exchange of declarative knowledge, the former being more tacit and idiosyncratic. Therefore, firms seeking to exchange tacit and complex knowledge may prefer to collaborate with more cognitively proximate partners than cognitively distant partners. In contrast, firms requiring technical advice for simple and autonomous knowledge can collaborate with partners having less cognitive proximity. This is because simple knowledge is less interrelated to other sub-systems in the organisation (Wong et al., 2008). However, a certain degree of knowledge overlap may still be necessary to establish partnership for simple and codified knowledge (Nooteboom et al., 2007).

Finally, process innovations require R&D collaborations with cognitively proximate partners to put existing ideas into practice, whereas product innovations require R&D collaborations with diversified partners to bring in varied knowledge and ideas (Dooley et al., 2015; Fitjar and Rodríguez-Pose, 2011). Thus, I submit the following hypotheses:

H2a: Cognitive proximity is positively associated with the formation of both the product and process innovation networks.

H2b: The impact of cognitive proximity is expected to be higher on the process innovations network than the product innovations network.

3.3.1.3 Social proximity as a determinant of product and process innovation networks

Social proximity refers to the embeddedness of actors in trustful social relations (Granovetter, 1985; Maskell and Malmberg, 1999; Boschma, 2005). It is often considered a prerequisite for interactive learning that facilitates the transfer of more sensitive and richer information (Leszczyńska & Khachlouf 2018). Owing to the diverse characteristics of product and process innovations, the role of social proximity may have a distinct relationship with the two innovation networks. I expect that while social proximity plays a positive and significant role for both the product and process innovation networks, the relative importance of social proximity may be higher for the formation of the process network than the product network.

Boschma (2005) pointed out that in a cooperation which is based on informal linkages, it is not market contracts that favour knowledge exchange; instead, it is trust that facilitates the smooth flow of knowledge among partners, especially when the knowledge is in tacit form. The transfer of tacit knowledge requires close interaction with the source of knowledge to interpret and acquire all components of the target knowledge (Nelson and Winter, 1982). Relational embeddedness promotes socialisation, which in turn facilitates the transfer of tacit knowledge (Uzzi, 1997). Dhanaraj et al. (2004) demonstrate a stronger impact of relational embeddedness on tacit knowledge transfer than on explicit knowledge. Hansen (1999) finds that social relations embedded in dense networks facilitate the transfer of tacit information. Similarly, Boari et al. (2017) suggest that friendship ties between individuals across organisations may play a crucial role in the transfer of tacit knowledge.

Similarly, firms require coordination among different organisational units to mobilise complex and systemic knowledge (Un and Asakawa, 2015). Trust and friendship-based ties may help overcome the multiple stage coordination problems that may arise owing to the systemic and complex nature of knowledge. Embeddedness in trustful relations promotes complex adaptation because actors can better identify and execute coordinated solutions (Uzzi, 1997). Sorenson et al. (2006) demonstrate that socially proximate actors are more likely to exchange moderately complex knowledge than socially distant actors. If the level of trust is low, as in the non-friendship-based relations, the management of tacit, systemic and complex knowledge may exacerbate coordination problems and eventually increase the burden on the focal actor.

In contrast, explicit knowledge can be exchanged relatively easily in the form of manuals and templates. Thus, it does not require a high level of trust, relational embeddedness and socialisation for its transfer (Dhanaraj et al., 2004). Moreover, product innovation is more observable and subject to external evaluation by customers (Damanpour, 2010). Customers demand novelty instead of efficiency. Therefore, firms tend to pursue exploratory-focused learning strategies to achieve novelty in products by introducing radical improvement (Un and Asakawa, 2015). Since, radical improvements require interaction with diverse partners and a variety of knowledge sources to achieve novelty (Fitjar and Rodríguez-Pose, 2011). Therefore, social proximity may play an important role in managing the diversity of relationships. Moreover, Subramaniam (2006) demonstrates that close interactions between individuals facilitate the transfer of both tacit and explicit knowledge. Hence, I submit the following hypotheses:

H3a: *Social proximity is positively associated with the formation of both the product and process innovation networks.*

H3b: *The impact of social proximity is expected to be higher on the process innovations network than the product innovations network.*

3.3.1.4 Organisational proximity as a determinant of product and process innovation networks

Organisational proximity refers to the similarity in terms of organisational routines and structures among collaborating partners (Broekel and Hartog, 2013). It is crucial for network formation because firms prefer to interact with others who are working under similar organisational structures. Moreover, similarity among firms' routines and organisational structures can make the transfer of knowledge easier from one place to another. The similarity in rules, procedures, practices, routines, structural equivalence, mechanism of coordination, and the set of interdependencies, are all related to the concept of organisational proximity (Aguiléra et al., 2012; Boschma, 2005). I expect that organisational proximity may have a positive and significant association with both the product and process innovation networks. However, I expect a higher impact on the process innovations network than the product innovations network.

Since the diffusion of complex and systemic knowledge requires a higher level of coordination between cooperating partners, firms may prefer to collaborate with more organisationally proximate partners when producing complex and tacit knowledge. Sharing similar organisational contexts and strong ties may facilitate the exchange of systemic and complex knowledge between partners (Boschma, 2005; Un and Asakawa, 2015). Hansen (1999) found that strong relationships between different units of a multiunit organisation facilitate the transfer of complex knowledge. Davids and Frenken (2018) also found the role of organisational proximity to be crucial in solving complicated production problems.

Moreover, partners sharing similar routines and operations can exchange tacit knowledge more easily (Boschma, 2005). For instance, subsidiaries of a multinational company or industry group share similar regulations and organisational contexts, hence the transfer of tacit knowledge between them is relatively easier than other more independent firms (Davids and Frenken, 2018). In a similar vein, Dyer and Neobaka (2000) illustrate how Toyota created a set of supplier networks, with similar operating contexts, to facilitate the transfer of tacit knowledge among members.

The exploitative-focused innovations aim to achieve incremental improvements by building on the existing organisational knowledge. On the contrary, exploratory-focused innovations aim to achieve radical improvements by interacting with a diversified set of knowledge (Benner and Tushman, 2003). In turn, firms pursuing exploitative learning strategies tend to establish strong ties because they require a deeper understanding of specific information, while firms that pursue exploratory learning strategies tend to form weak ties because they require a broader grasp of general information (Menzel et al., 2017; Rowley et al., 2000). Hence, I submit the following hypotheses:

H4a: *Organisational proximity is positively associated with the formation of both the product and process innovation networks.*

H4b: *The impact of organisational proximity is expected to be higher on the process innovations network than the product innovations network.*

3.4 Research context, data and methodology

3.4.1 Research setting

The empirical context of my study is the Lahore textile cluster in Pakistan, which is the second most populous city in Pakistan with a total population of around 11.07 Million in 2018 (Demographia, 2018) and accounts for about 10% of the entire textile and clothing firms in the country (PBS, 2013). The city is a hub of many industries including textile and clothing. The textile Industry is considered the backbone of the economy of Pakistan. It contributes to around 54% of the entire country's exports, employs 40% of the industrial workforce and also accounts for 8% of the total GDP (Pakistan Textile Policy, 2014-19). The industry is scattered across the country in the form of several clusters. The most prominent textile industrial clusters are located in the cities of Lahore; Faisalabad; Sheikhupura; Sialkot in the province of Punjab; and Karachi, Sukkur and Hyderabad in the region of Sindh.

Lahore is one of the most important cities in Pakistan. A recent study on the effects of agglomeration on socio-economic outcomes in Punjab-Pakistan indicates that Lahore has the second highest road density among the 29 clusters along with a significant amount of industrial agglomeration in the region (Azhar and Adil, 2019). According to the census of manufacturing industries conducted by the Pakistan Bureau of Statistics in 2005-06 (PBS, 2013), there are 170 textile and apparel firms in Lahore which employ around 350 workers on average. These firms are involved in almost all stages of the textile value chain, i.e., yarn manufacturing; knitted and woven fabric manufacturing; dyeing and printing and finishing of fabric; apparel and made-ups (Hamid et al., 2014). They are located mainly in four different locations in Lahore, i.e. Raiwind-Manga Mandi, Bhai Peru, Ferozepur Road and Defence Road. Azhar and Adil (2019) provide empirical evidence that shows a significant industrial agglomeration in Lahore and other parts of Punjab province. Studying the role of proximity in facilitating cooperation among local firms in Pakistan is interesting for several reasons.

First, prior research on industrial clusters in Pakistan indicates that, in general, most firms in the country are located in industrial zones (Nadvi and Halder, 2005; Rehman, 2016). Moreover, these studies have shown a positive association between cluster membership and inter-firm cooperation and innovation (ibid), which suggests that geographical proximity is an important factor that facilitates innovative collaboration among local firms.

Second, a strong culture of cooperation and support exists among cluster firms in Pakistan's textile and clothing sector (Islam, 2005). A key reason for this informal culture of collaboration between firms is the strong presence of a community of textile engineers in the local industry who are graduates of the oldest textile institute in the country, i.e. the National Textile University (NTU), Pakistan. NTU offers textile engineering degrees in five disciplines (spinning, weaving, processing, knitting and garments manufacturing) in line with the industrial requirements. These specialised engineers go into industrial units corresponding to their qualifications. The local industry recognises this community of textile engineers as "Textilian", "BSc's" or "Manawalian". Owing to this social and cognitive bonding among managers (textile engineers), they tend to support one another on a day to day basis to solve technical problems. This cooperation, in turn, contributes to knowledge circulation in the cluster.

The third critical aspect is that a small number of families own several textile firms in Pakistan (Haque, 2007). The embeddedness of firms in entrepreneurial family relations is also an important factor that promotes trust and cooperation among firms in the local cluster (Islam, 2005). This embeddedness nourishes the organisational proximity among firms owned by a single parent company (family group).

In this context, my study aims to investigate the role of different proximity dimensions in shaping the knowledge flows for products and process innovations among cluster firms. The next section presents my data collection.

3.4.2 Data collection

In order to investigate the impact of different dimensions of proximity on the formation of product and process innovation networks, I collected primary data at the firm level in the Lahore textile cluster. This was done via face to face interviews from the personnel responsible for the management of production operations and the development of new products and processes. In my study, the interviewee is either a technical director, a general manager or an R&D head. I chose these people for two reasons: First, they are the key decision makers in solving technical problems related to product and process innovations; second, they are the knowledge gate-keepers at the firm's manufacturing unit, which are responsible for the coordination of activities with the firm's other departments, e.g. marketing, finance and human resources as well as external partners. Huber (2013) maintains that the most important source of knowledge in a firm is the personal knowledge networks of senior-level managers.

In my study, the survey was not based on a sample of firms. Instead, data was collected from all large scale textile firms in the local cluster. From the total number of firms registered with All Pakistan Textile Mills Association (APTMA)[8], I first selected the total number of firms located in Lahore which was 84 in total. These data, however, contain some firms that had been temporarily out of operations for the last few months. Hence, I decided not to include those firms in my study which were not operational at the time of the

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[8] We surveyed only those firms that are registered with All Pakistan Textile Mills Association (APTMA) because these firms fall in the organised textile sector, which mostly include large scale firms that are required to maintain their operations and financial records owing to annual financial audits. The un-organised firms are mostly small size and some medium size firms as well, which are spread across the country with no requirement of maintaining financial records, thus making it difficult to verify their information from secondary sources. In order to apply the whole network approach, we limit our survey to only those firms that are registered with APTMA> http://aptma.org.pk/member.php

data collection exercise. Therefore, I surveyed 73 large scale active textile firms in Lahore.

A pilot study was also conducted before the actual data collection exercise. Four firms were visited during the pilot study that were located in the city of Lahore, Pakistan. This was done to test my instrument as well as to identify the key informants in the textile firms. The interviews sought information that would permit the development of quantitative indicators for measuring firm-level characteristics (e.g. firm size, manager qualification, exports performance) as well as relational variables. In addition to the interviews, I collected information from secondary data sources, such as companies' annual reports, various government reports, industry reports and websites of companies and other departments. In fact, I triangulate the data. Bell et al. (2018: 365) state that triangulation is a process that entails using multiple sources of data to cross-check findings. These sources helped us validate the information collected via interviews and also contributed to the construction of some of the explanatory and control variables (e.g. firm age, innovation capability and technology profiles).

I collected relational data using roster recall methodology (Wasserman and Faust, 1994). In this method, each firm was provided with a complete list (roster) of the other firms in the cluster. I asked respondents to choose from a roster of 73 firms to which respondents regularly asked for technical advice. Scholars have widely used this methodology to collect relational data (Balland et al. 2016; Boschma and Ter Wal 2007; Giuliani and Bell 2005, Giuliani 2007; Giuliani, 2013). This approach is particularly useful for the collection of whole network data because it reduces selectivity bias in the responses of personnel owing to memory effects (Molina-Morales et al., 2015). The next section will explain the operationalisation of key variables.

3.4.3 Measures

3.4.3.1 Explanatory variables

Geographic proximity is usually measured as the distance between firms in either physical distance, travel time or simply by co-location (Balland, 2012; Broekel and Boschma, 2012; Molina-Morales et al., 2015). I calculate the geographic distance between firms in kilometres using the GPS coordinates. UCINET 6 software provides a function to convert coordinates to distance (Borgatti et al., 2002). I obtain the maximum of 1.82 and minimum 0 by computing the natural logarithm of the distance between firms. Subsequently, I inverse the distance to obtain the proximity variable (Boschma et al., 2014; Boschma et al., 2016)). This was done by subtracting each value with the maximum value, i.e., 1.82 km in my case. Eventually, my maximum value for geographic proximity is between 0 for the most distant firms and 1.82 km for the most proximate ones. The formula for geographic proximity between firm 'i' and 'j' is as follows:

$$\text{Geographic Proximity}_{ij} = 1.82 - \ln(\text{distance}_{ij})$$

Cognitive proximity can be measured in several ways. Scholars measure it using the similarity in the NACE codes (Molina-Morales et al., 2015; Usai et al., 2015), or similarity in the technological and knowledge base of firms (Broekel and Boschma, 2012; Quatraro and Usai, 2017a). I measure cognitive proximity using cosine similarity index between firms' technology profiles as defined in the Pakistan Standard Industrial Classification (PSIC)[9]. In other words, it is the technological proximity between firms. I then used the following formula to calculate the cosine similarity index[10] between the eight industrial codes associated with the textile industry:

$$\text{Cosine Similarity (A, B)} = \cos(\theta) = \frac{A \bullet B}{\|A\|\|B\|}$$

[9] Pakistan Standard Industrial Classification (PSIC) and the definition of each class can be found at: http://www.pbs.gov.pk/sites/default/files/other/PSIC_2010.pdf (Last accessed 1st January, 2019)

[10] We use UCINET6 software to calculate cosine similarity index

Where ||A|| is the Euclidean norm of technology vector, A = (A_1, A_2,......,A_8), defined as $\sqrt{A_1^2 + A_2^2 + \cdots + A_8^2}$. Similarly, ||B|| is the Euclidean norm of technology vector, B = (B_1, B_2,.......,B_8), defined as $\sqrt{B_1^2 + B_2^2 + \cdots + B_8^2}$. The final value estimates the cosine of the angle between vector two vectors. A cosine value of 0 means that two vectors are at 90 degrees and have no match, while a cosine value of 1 means two vectors are at 0 degrees and have a perfect similarity (Kellstedt and Whitten, 2013). In total, eight technologies appear in my data set. Table 3-3 provides information on the technology profiles of firms, i.e. the number of firms involved in each textile technology as per the PSIC database.

Table 3-3 Technology profile of firms

Firms' technology profile *(as per PSIC Codes)*	Number of firms (%), *N=73*
Spinning (1311)	37 (26%)
Weaving (1312)	21 (14%)
Textile Processing (1313)	36 (25%)
Knitting (1391)	8 (6%)
Home Textile Made-ups (1392)	7 (5%)
Embroidery work (1399)	13 (9%)
Apparel & Garments excl. Knitted (1410)	18 (12%)
Knitted Apparel & Garments (1430)	5 (3%)

Social proximity is measured in two ways. My first measure is based on university affiliation that is shown to be an important driver of network formation (White, 2011). It is a binary variable, which takes the value '1' if managers/directors of collaborating firms have graduated from the same university, and '0' otherwise. In my case, I ask managers about their affiliation with the National Textile University (NTU), Faisalabad. Since I have already explained in the research setting that NTU graduates have strong social bonding with one another and also dominate the local industry, I expect high cooperation among NTU graduates. I name this variable as 'social proximity-same university'. For the second measure, I sought information on the past three employers of managers/directors. Sharing common employment history is crucial for collaboration and a relevant sign of social proximity (Flemming and Marx, 2006). It is also a binary variable which takes the value 1 when collaborating partners share employment history, and 0 otherwise. I adopted this idea from Broekel and Boschma (2012) who measured the social proximity between firms based on the CEO's past affiliations with the Fokker Company. I name this variable as 'Social proximity-past employer'.

Organisational proximity is also a binary variable in my study. It takes the value 1 when collaborating firms belong to a single parent organisation or the same industrial group, and 0 otherwise. This measure is widely used in previous research (Boschma et al., 2014; Molina-Morales et al., 2015). As discussed in the research setting, several firms in the local textile cluster are owned by a small number of families, which operate as a group of companies. Hence, I consider partners to be organisationally proximate if they belong to the same industrial group.

3.4.3.2 Dependent variables

In this study, I aim to investigate the effect of proximity dimensions on the formation of product and process innovation networks. Each network can be represented as binary $n*n$ graphs $x = (x_{ij})$, where $x_{ij}=1$ when actor *'i'* discloses a technical advice link to actor *'j',* otherwise $x_{ij}=0$. My first dependent variable is a *73*73* socio-matrix for *'product innovations network'*, which is a dichotomous variable and indicates whether firm *'i'* or *'j'* mention the other as a source of technological knowledge for new products development. Similarly, my second dependent variable is a *73*73* socio-matrix for *'process innovations network'*, which is also a dichotomous variable and indicates whether firm *'i'* or *'j'* mention the other as a source of technological knowledge for new process development.

Figure 3-2a and 3-2b provide the graphical representation of process and product innovation networks respectively. The colour of nodes represents the different geographic zones in the local cluster. These firms are located in four different geographical zone. It seems that geographical proximity is relevant for facilitating collaborations among firms in both the product and process innovations, since the same colour nodes appear to be connected to one another, as shown in figure 3-2. A social network analysis software package UCINET 6 was used to analyse the relational data (Borgatti, Everett, & Freeman, 2002).

I asked the following two questions to gather relational data about product and process innovation advice sharing;

a) *When you need technical advice on product development/innovation, to which of the local firms mentioned in the roster (list) do you turn?*
b) *When you need technical advice on process improvement/innovation, to which of the local firms mentioned in the roster (list) do you turn?*

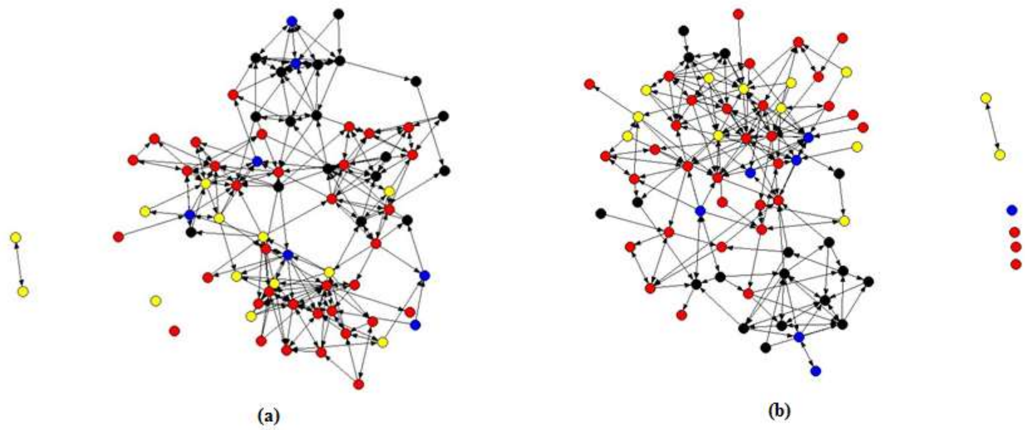


Figure 3-2 (a) Process innovation network; (b) product innovation network (Colour represent different geographical zones)

3.4.3.3 Control variables

I control for several variables that can affect the formation of networks. First, I control for the *age* of firms because several studies show that similar age firms are likely to interact with each other (Molina-Morales et al., 2015). I measure firm age by taking the square root of the years. Age is a continuous variable in my data in vector form. Second, I control for the *size* of firms and measure it by the number of employees. I calculate the natural log of the size variable. Size is a continuous node level variable. Following Broekel and Hartog (2013), I create a dyadic variable for size by summing up the size of two firms. Third, I control for the *joint R&D activities* of the firm. Firms involved in a joint research project may be more open and hence more likely to form ties with other research-oriented firms (Giuliani and Bell, 2005). Joint R&D is a binary variable that takes the value ‘1’ when a firm indicates involvement in joint research projects and ‘0’ otherwise. Fourth, I control for the *manager’s qualification*. In my data, I have engineering graduates, business graduates and non-degree holder managers. Fitjar and Rodríguez-Pose (2011) show that the education level of a manager influences the cooperation behaviour of firms. Fifth, I control for *export performance*. Export-oriented firms may be more likely to cooperate with other similar firms. Giuliani (2010) in her study on wine clusters shows significant cooperation among export-oriented firms. It is a dichotomous variable in my study that takes the value 1 for the exporter and 0 otherwise. Finally, I control for the *trade memberships* of firms. Houghton et al. (2009) argue that memberships in a trade association are an important type of external network. They find a significant positive correlation between trade association participation and knowledge acquisition by firms. Indeed, trade association participation offers socialisation opportunities to firms’ executives to exchange ideas with one another about new products and technologies. In my data, it is a continuous variable with a minimum value of 0 and a maximum of 12. I transform this variable to capture both the sender and receiver effect.

Table 3-4 QAP correlations of the dyadic proximity variables (5000 permutations)

		1	2	3	4	5
1	Cognitive proximity					
2	Geographic proximity	0.08**				
3	Organisational proximity	0.06*	0.14**			
4	Social proximity (same-university)	0.03	0.06**	0.04*		
5	Social proximity (past-employment)	0.10***	0.12***	0.04*	0.05***	

Table 3-4 presents the descriptive statistics of the dyadic explanatory and control variables. Geographic proximity is a continuous variable which takes the value in kilometres, i.e. 1.82 km for the most distant partners and 0 km for the closest ones. Similarly, cognitive proximity is also a continuous variable, which is an index value that would take the value 1 for perfect similarity and 0 for perfect dissimilarity. In contrast, organisational and social proximity are dichotomous variables. The value of organisational proximity is between ‘0’ and ‘1’, where ‘1’ indicates that collaborating partners belong to the same industrial group and ‘0’ otherwise.

Similarly, social proximity takes the value ‘1’ when the top manager is a graduate of NTU and ‘0’ otherwise. The second measure of social proximity takes the value ‘1’ when managers share previous work experience with collaborating partners and ‘0’ otherwise. Table 3-5 presents the correlation among the proximity variables, which indicate a significant correlation among most of the proximity variables. However, the proximity variables are not highly correlated. The correlation results are in line with previous research (e.g. Balland et al., 2016), which find a weak correlation among the proximity dimensions.

Table 3-5 Descriptive statistics of the dyadic variables

Variable	Measurement	Type of data	SD	MIN	MAX
Joint R&D activities	Participate in same project	Dichotomous	0.47	0	1
Exports performance	Whether firm is an exporter	Dichotomous	0.50	0	1
Firm Age	Square root of age in years	Continuous	1.24	1	7.48
Firm Size	Log of no of employees	Continuous	0.312	2.6	3.85
Manager qualification	Degree level of manager	Categorical	0.53	1	3
Trade memberships (Sender)	Sender of a tie, memberships	Continuous	2.23	0	12
Trade memberships (Receiver)	Receiver of a tie, memberships	Continuous	2.23	0	12
Geographic proximity	Inverse log-distance in km	Continuous	0.422	0	1.822
Cognitive proximity	Cosine Index	Continuous	0.388	0	1
Social proximity (university)	Manager's affiliation with NTU	Dichotomous	0.49	0	1
Social proximity (employment)	Shared past employment	Dichotomous	0.082	0	1
Organisational proximity	Same Parent Company	Dichotomous	0.136	0	1

3.5 Estimation model

To test the hypothesis, this study employs multiple regression quadratic assignment procedures (MRQAP). MRQAP is a network regression technique that uses a permutation method to assess the statistical significance and interdependencies of relational variables (Broekel et al., 2014). Relational variables describe the link between two actors, i.e. the extent to which they are distinct, similar, or share specific attributes (Broekel and Boschma, 2012). A predominant characteristic of relational data is the lack of independence among observations, which limits the use of standard regression techniques (Krackhardt, 1988). The difference between standard regression and the MRQAP model is that the former demands independence of observations, while the latter technique is capable of dealing with the lack of independence among observations (Scott and Carrington, 2011). Hence, in the MRQAP model both the dependent and independent variables are n x n relational matrices instead of vectors (Broekel and Hartog, 2013). In order to test the hypothesis using MRQAP, multiple relational matrices (as explanatory variables) are used to predict a dependent relational matrix (Robins et al., 2012). Snijders (2011) argues that MRQAP is useful when the focus of research is exclusively on the effects of predictor variables.

The p-value or the significance of the test is estimated by permuting the rows and columns of the matrices thousands of times (Dekker et al., 2007; Krackhardt, 1987). The model fit and regression coefficients of the observed data are compared to coefficients obtained through extensive permutation of rows and columns (Pinheiro et al., 2016). For example, if an initially estimated coefficient value remains greater than 95% of the estimates obtained through permutations, the original coefficient estimate is considered as significant at 0.05 level (Borgatti et al., 2013). In this study, I employ MRQAP, 'semi-partialling plus' method because it is considered robust in dealing with multi-collinearity problems associated with MRQAP analysis (Broekel and Boschma, 2012; Dekker et al., 2003). In the present study, QAP routines were performed with 5000 permutations.

The basic form of the MRQAP model is estimated using the following equation:

$$\boldsymbol{Y_{ij}} = \boldsymbol{Ln}\left(\frac{Y}{1-Y}\right) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 X_1} + \boldsymbol{\beta_2 X_2} + \boldsymbol{\beta_3 X_3} + \boldsymbol{\beta_4 X_4} + \boldsymbol{\beta_5 X_5} + \boldsymbol{\beta_6 X_6} + \boldsymbol{\varepsilon} \quad \text{------ Eq.1}$$

Where, '$\boldsymbol{Y_{ij}}$' is the dependent socio-matrix or network, while X1, X2, X3, X4, X5 are the other socio-matrices that influence the behaviour of 'Y'. In the equation β0,, is the constant term and '$\boldsymbol{\varepsilon}$' is the residual matrix. Moreover, β1 is the coefficient of X1 'geographic proximity', β2X2 'cognitive proximity', β3X3 'organisational proximity', β4X4 'social proximity (past-experience)', β5X5 'social proximity (same-university)', and β6X6 'controls' and ε is the error term. The size of these coefficients provide the measure of the relative importance of each of the proximity dimensions on the likelihood of tie formation.

3.6 Results and discussion

This section presents the results of the paper and discusses the impact of different proximity dimensions on the formation of product and process innovation networks. Before discussing the research hypothesis, the paper presents the structural descriptive statistics of the two innovation networks in Table 3-6. The number of edges (links) in the process and product innovation networks are 259 and 206 respectively. The average degree of process and product innovation networks is 3.55 and 2.82 respectively, which indicates that firms ask process innovation-related advice from about four different firms, while they ask product innovation-related advice from about three different firms. The density of the process network (0.049) is slightly higher than the density of the product network (0.039).

Table 3-6 Structural descriptive statistics of product and process innovation networks

	Nodes	No. of ties	Average degree	Density
Product innovation network	73	206	2.82	0.039
Process innovation network	73	259	3.55	0.049

I also computed the correlation between product and process innovation networks. The results obtained from the QAP correlation is reported in Table 3-7. The correlation between the two networks is 0.448, which indicates that 45% of product and process innovation ties overlap with each other. This shows that firms tend to seek advice from the same partners for both product and process innovations in 45% of instances, while 55% of times they seek advice from different partners for product and process innovations. This is an interesting finding; however, the focus of this paper is not to examine the overlap between product and process innovation networks, rather it aims to investigate the impact of proximity dimensions on the formation of product and process innovation networks.

Table 3-7 Correlation between product and process innovation networks

Network type	SD	Pearson Correlation (5000 permutations)
Product vs Process Network	0.0149	0.448*** (0.000)

Table 3-8 QAP-logit network regression model for process innovation network (N=73)

Model 1	Estimate	Exp (b)	Pr (<=b)	Pr (>=b)
Intercept	-7.25***	.0007	0.000	1.000
Control				
Age	-0.02	0.97	0.45	0.54
Size	0.003	1.00	0.68	0.31
Exports performance	0.30*	1.35	0.96	0.032
Joint R&D activities	0.33⁺	1.40	0.91	0.08
Manager qualification	-0.24	0.78	0.12	0.87
Trade memberships (receiver effect)	0.12**	1.12	0.99	0.005
Trade memberships (sender effect)	0.07*	1.07	0.95	0.050
Proximity Effects				
Geographic proximity	0.48*	1.62	0.96	0.032
Social proximity (same-university)	0.47**	1.60	0.99	0.004
Social proximity (past-experience)	2.07***	7.97	1.000	0.000
Organisational proximity	2.39***	10.9	1.000	0.000
Cognitive proximity	3.48***	32.6	1.000	0.000

The goodness of fit statistics

Null deviance: 7286.363 on 5256 degrees of freedom
Residual deviance: 1517.87 on 5243 degrees of freedom
Chi-Squared test of fit improvement:
5768.87 on 13 degrees of freedom, p-value 0
AIC: 1543.493 BIC: 1628.866
Pseudo-R^2 Measures:
(Dn-Dr)/(Dn-Dr+dfn): 0.523
(Dn-Dr)/Dn: 0.791
Total fraction corrected: 0.956

⁺sig at 0.1,*sig at 0.05, **sig at 0.01, *** sig at 0.001

Table 3-9 QAP-logit network regression model for product innovation network (N=73)

Model 2	Estimate	Exp (b)	Pr (<=b)	Pr (>=b)
Intercept	-7.40***	.0006	0.000	1.000
Control				
Age	0.029	1.02	0.60	0.40
Size	0.008⁺	1.00	0.92	0.08
Exports performance	-0.26⁺	0.76	0.06	0.94
Joint R&D activities	0.63**	1.89	0.99	0.006
Manager qualification	-0.13	0.87	0.26	0.734
Trade memberships (receiver effect)	0.10*	1.10	0.97	0.03
Trade memberships (sender effect)	0.03	1.03	0.78	0.22
Proximity Effects				
Geographic proximity	0.79***	2.21	0.99	0.001
Social proximity (same-university)	0.51**	1.67	0.99	0.004
Social proximity (past-experience)	1.89**	6.62	0.99	0.002
Organisational proximity	1.88***	6.59	1.000	0.000
Cognitive proximity	2.76***	15.9	1.000	0.000

The goodness of fit statistics

Null deviance: 7286.363 on 5256 degrees of freedom

Residual deviance: 1360.96 on 5243 degrees of freedom

Chi-Squared test of fit improvement:

5925.403 on 13 degrees of freedom, p-value 0

AIC: 1386.403   BIC: 1472.333

Pseudo-R^2 Measures:

(Dn-Dr)/(Dn-Dr+dfn): 0.529

(Dn-Dr)/Dn: 0.813

Total fraction corrected: 0.96

⁺sig at 0.1,*sig at 0.05, **sig at 0.01, *** sig at 0.001

In order to test my research hypothesis and explain how proximity dimensions impact the formation of product and process innovation networks, I perform MRQAP logit regression analysis (Broekel and Boschma, 2012; Dekker et al., 2003; Krackhart, 1987) and test two models. Table 3-8 shows the results of the MRQAP analyses for the process innovations network as the dependent variable, while Table 3-9 shows the results of the MRQAP analysis for the product innovation network as the dependent variable.

In my analysis, all parameter estimations are based on 5000 permutations. My results indicate that all proximity dimensions show a positive and significant impact on the formation of both product and process innovation networks. The parameter estimates of geographical, social, organisational and cognitive proximity are positive and significant for both networks. These results confirm four of my research hypotheses, i.e. H1a, H2a, H3a and H4a. The pseudo R-square and other goodness of fit statistics reveal that both models perform well in explaining the likelihood of linkage formation among firms for the exchange of product and process related knowledge. These findings are in line with several previous studies which found a positive and significant relationship between multidimensional proximity and network formation (e.g. Aguiléra et al., 2012; Balland, 2012; Balland et al., 2016; Boschma et al., 2014; Broekel and Boschma, 2012; Lazzeretti and Capone, 2016).

Geographic proximity shows a positive and significant impact on both process and product innovation networks when controlling for other proximities. This finding supports my hypothesis *H1a*. Moreover, this finding is consistent with several studies that suggest that geographic proximity facilitates the transfer of not only tacit knowledge but also codified knowledge (e.g. Bathelt et al., 2004; Boschma, 2005; Moodysson et al., 2008). I also hypothesised a stronger impact of geographic proximity on the process innovations network as compared to the product innovation network. However, the parameter estimates [given in Tables 3-8 & 3-9] indicate that these findings are contradictory to my theoretical predictions.

The coefficient for the product innovation network is relatively higher ($\beta = 0.79$) than the coefficient for the process innovations network ($\beta = 0.48$). This result suggests that firms are more likely to seek advice from geographically proximate partners for product innovations than process innovations. These results do not support my research hypothesis *H1b.* Although this finding is rather unexpected, it is in line with some previous studies. For instance, Freel (2003) found a decrease in partnerships with increased geographical distance among incremental product innovators. Moreover, Dooley et al. (2015) show that firms tend to interact with geographically proximate partners when their focus is on exploitative innovations. Since the context of my study is a mature industrial cluster where firms tend to develop exploitative (incremental) products and process innovations, this might be one of the reasons I find a stronger association between geographical proximity and formation of the product innovations network.

As per my expectation, cognitive proximity is highly relevant for the process innovations network. The coefficient is positive ($\beta = 3.48$) and significant ($p < 0.001$). Similarly, the impact of cognitive proximity on the product innovations network is positive ($\beta = 2.76$) and significant ($p < 0.001$). However, the parameter estimate for the product innovations network is relatively lower than the process innovations network. This result indicates that firms tend to link more with technologically similar partners when they seek advice on process innovations (odds=32.6) as compared to product innovations (odds=15.9), thereby confirming my research hypothesis *H2b*. These results are also in line with other studies, which suggest that collaborative innovation activity is highest among cognitively proximate partners for exploitation-focused innovations (Dooley et al., 2015), which is the characteristic of process innovations. Moreover, these findings are consistent with previous research on the diffusion of technical knowledge, which argues that cognitive proximity among collaborating partners is crucial for the diffusion of complex, tacit and idiosyncratic knowledge (Balland et al., 2016; Balland and Rigby, 2017).

My study shows that social proximity also influences the formation of both process and product innovation networks. The coefficient for social proximity (past-experience) is positive ($\beta = 2.07$) and significant ($p < 0.01$) for the process innovations network. Similarly, the coefficient is positive ($\beta = 1.89$) and significant ($p < 0.01$) for the product innovations network. As hypothesised, the parameter estimate for the process innovations network is relatively higher than that for the product innovations network. These findings are in line with previous studies that argue that the transfer of tacit knowledge requires high social proximity among partners (Boari et al., 2017; Dhanaraj et al., 2004; Hansen, 1999). I also computed a second variable for social proximity (same-university), which is also positive and significant ($p < 0.01$) for both the process and the product innovation networks. However, in this case, the parameter estimate for the product innovations network (0.51) is almost the same as for the process innovations network (0.47). Therefore, these results partially confirm my research hypothesis *H3b*. This is an interesting finding that suggests that university alumni play an equally important role for different types of exchanges.

Concerning organisational proximity, I find a positive ($\beta = 2.39$) and significant ($p < 0.001$) impact on the process innovations network. Similarly, my results show a positive ($\beta = 1.88$) and significant ($p < 0.001$) impact on the product innovations network. However, the magnitude of the parameter estimate is relatively lower for the product innovations network than the process innovations network. This result indicates that firms that belong to a single umbrella organisation tend to seek advice from one another for both product and process innovation networks. However, the likelihood of tie formation between organisationally proximate partners is relatively higher for process innovations (odds = 10.9) than product innovations (odds = 6.59). This result confirms my research hypothesis *H4b*. My study confirms the findings of previous studies, which suggest high organisational proximity facilitates the transfer of tacit knowledge (Davids and Frenken, 2018; Hansen, 1999).

While some of my results confirm findings in other studies, the predominant contribution of my research is studying the distinctive impact of multiple proximity dimensions on multiple innovation networks. On the one hand, I demonstrate that the impact of social (past experience), organisational and cognitive proximity dimensions on the process innovations network is relatively higher than the impact on the product innovations network. On the other hand, I show that geographical proximity has a relatively higher impact on product innovation network. Figure 3-3 graphically represents the parameter estimates of proximity dimensions for process and product innovation networks respectively. It shows the difference among the coefficients of proximity dimensions for product and process innovation networks. Moreover, cognitive proximity has the highest impact on the formation of the two networks followed by organisational, social and geographic dimensions.

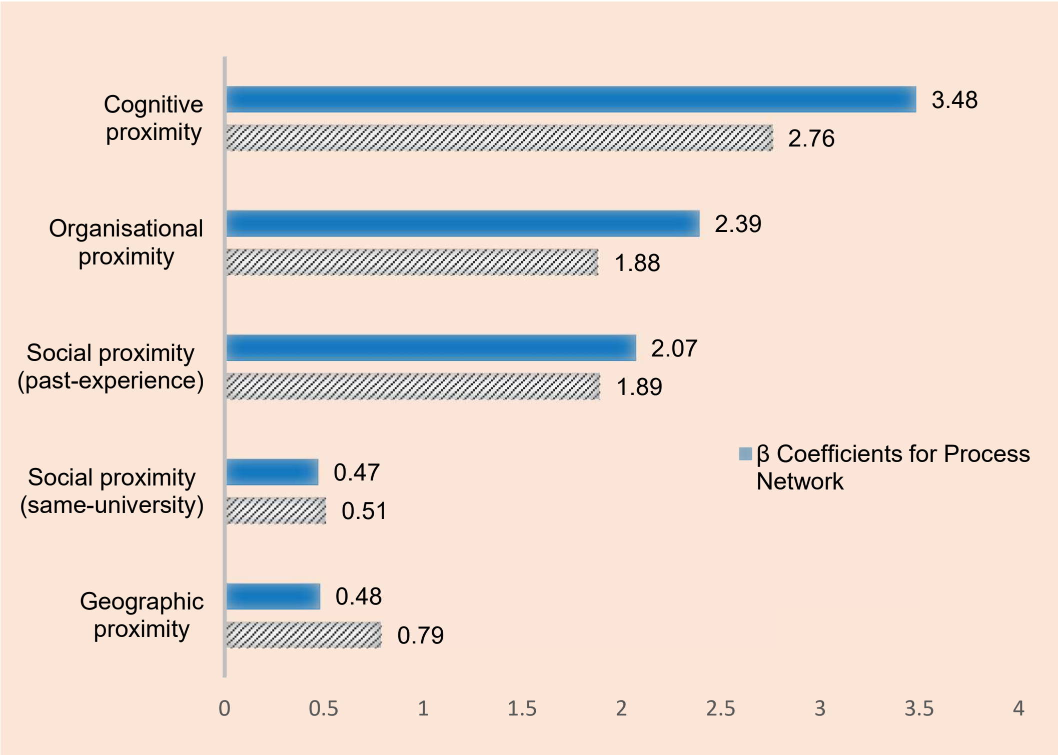


Figure 3-3 Graphical representation of proximity estimates for product and process innovation networks

In addition to proximity variables, I also test for control variables. In model 1, I tested the relationship between control variables and the formation of the process innovations network. Similarly, in model 2, I tested the relationship between control variables and the product innovations network. My first control variables are age (absolute difference), which is negative for the process innovations network and positive for the product innovations network; however, it is not significant for any of the two networks. The second variable is the size (number of employees), which is positive for both networks but weakly significant ($p<0.1$) for the product innovations network. I also controlled for the export orientation of firms. This variable is positive ($\beta = 0.30$) and significant ($p < 0.05$) for the process network; however, it is negative (-0.26) for the product network ($p<0.1$), which implies that the export-oriented firms that are involved in product innovations are less likely to collaborate with other export-oriented firms and vice versa for process innovations. In addition to that, I controlled for joint R&D activities. This variable is positive (0.63) and highly significant ($p < 0.01$) for product network, while positive (0.33) and weakly significant ($p < 0.1$) for the process network. This result suggests that participation in joint R&D projects with other firms increases the likelihood of tie formation in both product and process developments. The coefficient for the product innovations network is twice as much as the coefficient for the process innovations network. I also controlled for managerial qualifications (absolute difference), which is negative but not significant for both networks. This result suggest that more qualified managers may be less likely to interact with less qualified managers; however, my results are not significant; hence, I cannot confirm these findings. Finally, I control for trade memberships (sender/receiver effects). Taking into consideration the memberships of trade associations, alter-memberships in the trade associations are not likely to facilitate linkage formation in the product network, whereas the coefficient for the process network is positive ($\beta = 0.07$) and significant ($p < 0.05$). On the contrary, if the receiver of the tie hold memberships is in several trade associations, there is a significantly higher likelihood of its tie formation both in the development of process ($\beta = 0.12$, $p<0.01$) and product innovations ($\beta = 0.10$, $p<0.05$).

3.7 Conclusion

This paper has looked at whether the impact of geographic, organisational, social and technological proximity vary according to the type of innovation network. In particular, I studied the influence of these proximity dimensions on the formation of product and process innovation networks. I first proposed a positive relationship between proximity dimensions and both innovation networks and then expected a relatively higher impact of all proximity dimensions on the process innovations network as compared to the product innovations network. The key tenet in this paper was that the relative difference in the characteristics of product and process innovations might affect the relationship between proximity dimensions and the formation of the two innovation networks.

My expectations were largely confirmed when it comes to analysing the positive relationship between proximity dimensions and the two innovation networks. I find a positive and significant influence of proximity dimensions on the formation of both product and process innovation networks. Concerning the differing impact of proximity dimensions on the two networks, on the one hand, I find that the impact of social, organisational and cognitive (non-spatial) proximity is relatively stronger in the process innovations network. On the other hand, I find that geographical proximity shows a higher impact on the product innovations network. Although my results largely support my theoretical predictions, findings related to geographical proximity contradict my prediction. Thus, I invite further studies to explore this idea and investigate how the relationship between proximity dimensions and product and process innovations operate in other industrial sectors as well as geographical contexts.

This study makes several contributions to the extant literature. First, it contributes to the recent debate on innovation networks and proximity dynamics, which suggest that the impact of proximity dimensions may have a distinctive relationship with different types of knowledge flows and innovation networks (e.g. Balland et al., 2016; Boschma et al., 2015; Davids and Frenken, 2018; Leszczyńska and Khachlouf 2018; Quatraro and Usai, 2017a; 2017b). In this study, I tested the relationship between proximity dimensions and product and process innovation networks. My study provides evidence that proximity dimensions exercise a distinct influence on the formation of product and process innovation networks because these two innovation types differ from each other on various dimensions (e.g. knowledge codification; substitution; rareness and valuation).

Second, this paper contributes to the research on the geography of complex knowledge and innovation activities (Balland and Rigby, 2017; Ferru and Rallet, 2016; Grabher et al. 2018; Grillitsch and Rekers, 2016; Shearmur and Doloreux, 2015; Shearmur et al., 2016), which argue that geography matters in the creation and diffusion of innovation activities. Moreover, geographical proximity plays a more crucial role in the transfer of tacit and complex knowledge than the transfer of codified and simple knowledge. Since I theorise that the knowledge associated with process innovations tends to be more complex and tacit than with product innovations, my study provides evidence that the role of geography is crucial for the transfer of knowledge for both product and process innovations.

Finally, I contribute to the research on network multiplexity (Bliemel et al., 2014; Lee and Lee, 2015; Leenders and Dolfsma, 2016; Mazzola et al., 2016; Ram & Lori, 2014; Shipilov, 2012; Shipilov et al., 2014), which suggests that actors are connected to one another via more than one relationship and that they often share more than one type of resource. In my work, I studied the formation of product and process innovation networks and argue that firms tend to seek technical advice from each other about both types of innovation networks. I provide empirical evidence that 45% of product and process advice linkages overlap in my relational data, which suggests that almost half of the time firms tend to seek product and process advice from the same actors.

However, my main purpose was to investigate the impact of multiple proximity dimensions on the formation of multiple networks. In this regard, my main contribution that geographical, organisational, social and cognitive dimensions of proximity distinctively influence the formation of product and process innovation networks is of immense importance.

Chapter 4 Formation and dynamics of product and process innovation networks: Evidence from a textile cluster in Pakistan

4.1 Introduction

An industry cluster is a group of geographically proximate firms from the same or related industry (Becattini, 1990; Bell, 2005). Informal networks—heterogeneous groups of interpersonal contacts—play a crucial role in promoting innovative activities in industry clusters (Harrison, 1994; Porter, 1990, 1998). These networks encourage frequent social interactions among firms which eventually facilitate information and knowledge exchange (Huber, 2012). The advantages of having broad and diverse social relations are well established in network and cluster studies (Granovetter, 1985; Powell and Grodal, 2005). Prior research in this field has focused on the impact of the structural properties of these networks on the innovative outcome of actors (Boschma et al., 2014). More recently, I have witnessed dramatic growth in studies on the genesis, dynamics and evolution of these networks (Ahuja et al., 2012; Gluckler, 2007; Giuliani, 2013; Balland et al., 2013; Balland et al., 2015). Despite numerous contributions in this field, little attention has been paid to the formation and dynamics of multiple and multiplex networks (Balland et al., 2016; Brailly, 2016; Brennecke and Rank, 2017; Shipilov, 2012).

The term multiplex networks refers to the connectedness among actors via more than one relation (Shipilov 2012). It has been acknowledged that having a central position in a network maximises the flow of information and hence affects the desired outcome. Bell (2005) found that on one hand, a central position in the managerial network increases the innovative performance of firms. On the other hand, a central position in the institutional network does not affect firms' innovative performance. Giuliani (2007) revealed that the structural properties of business networks is different from the properties of technical networks. The relations established among firms to gather business information are common, whereas relationships established among a similar set of firms to solve technical problems are selective. Balland et al. (2016) showed that various proximity dimensions and network endogenous effects distinctively influence the formation of business and technical advice networks. These findings suggest that the network type plays an important role in determining the effect of key variables in the process of network formation, and therefore, it is essential to study the formation of networks, making a careful distinction between different types of networks.

In this regard, some economic geographers suggest studying the knowledge spillovers in radical and incremental innovations. They suggest exploring whether the diffusion of these two innovation types are influenced in the same way by the dyadic attributes, network structural properties and the individual attributes of actors (Boschma et al. 2015). The central idea is that the sources of radical innovations may be different from the sources of incremental innovations, and therefore firms may collaborate with different types of partners. Similarly, Ferru and Rallet (2016) suggest that the organisational choices related to product and service innovations could affect the decision of a firm on the spatial configuration of its innovation process. In this paper, I aim to extend this line of inquiry by examining how firm-level attributes, dyadic attributes and endogenous network mechanisms influence the formation of product and process innovation networks.

I argue that it is essential to focus on product and process innovations because they play a crucial role in the competitiveness of both the local firms and the industrial district (Carbonara, 2017, Un and Asakawa, 2015). Understanding the drivers and antecedents of the product and process innovation networks may help firms' better coordinate knowledge production activities, which in turn may influence firms' competitiveness in clusters. Moreover, prior research on product and process innovations suggests that these two innovation types embody different knowledge characteristics (Casanueva et al. 2013; Gopalakrishnan et al., 1999; Hatch and Mowery, 1998; Krzeminska and Eckert, 2015; Terjesen and Patel, 2017; Un and Asakawa, 2015). Owing to these distinctive knowledge characteristics of the two innovation types, node-level (e.g. absorptive capacity), dyad-level (e.g. business relations) and structural-level variables (e.g. degree centrality) may play a distinct role in facilitating R&D collaborations for product and process innovations.

In doing so, I aim to contribute to the literature investigating the underlying forces behind the formation and dynamics of multiplex networks (Balland et al., 2016; Brailly, 2016; Brennecke and Rank, 2017; Lee and Lee, 2015). I also contribute to the debate on social selection and network self-organisation, which argues that firms and individuals select partners by similarity in individual attributes and that network ties tend to pattern themselves in certain ways (Rank et al., 2010; Robins, 2009; Robins et al., 2012). I also contribute to the studies on exponential random graph models (Goodreau, 2007; Haris, 2014; Hunter et al., 2008) by applying this methodology to the context of an emerging country. Finally, I contribute to the literature on social networks in emerging countries, which lacks empirical contributions (AlKuaik, 2017; Chuang and Schechter, 2015).

The structure of the paper is as follows: The next section provides a review on the drivers of network formation and why it might be essential to study the network of product and process innovation; in section three, I present my research hypothesess; the data and methodology are presented in section four, and the results are discussed in the fifth section; I conclude in the last part with the limitations of the current study and suggestions for future research.

4.2 Literature review

4.2.1 External knowledge sources of product and process innovations

The extant literature on knowledge sourcing suggests that in order to develop product and process innovations, firms rely heavily on knowledge exchange with external parties (Chesbrough 2003; Landry et al., 2002; Laursen and Salter 2006; von Hippel 2005). These partners may include suppliers, customers, universities, competitors and other players (Laursen et al., 2012). Gemunden et al. (1996) argue that these external partners play a distinctive role in developing new products and new processes. For instance, the authors found interactions with both customers and suppliers to be crucial for product innovation success, whereas the role of consultants and universities were considered as more important for process innovations. In a similar vein, several studies have shown that product and process innovations demand collaborations with different kinds of external partners. For instance, Freel and Richard (2006) found that cooperation with suppliers and universities plays an important role in the introduction of process innovations, whereas interactions with customers and the public sector were found to be more important for product innovations. In the context of the construction industry, Reichstein et al. (2008) found that collaborations with suppliers significantly improve the likelihood of process innovations, whereas cooperation with customers tended to play a more important role in product innovations. Research also showed that R&D cooperation with customers and universities plays a vital role in developing product innovations (Kang and Kang, 2010).

More recently, research on the external knowledge sources of product and process innovations suggests that upstream suppliers play a significant role in the introduction of process innovations, whereas competitors and downstream customers are found to be more critical in the introduction of product innovations (Antonelli and Fassio, 2016). Drawing attention towards the functional perspective on learning and innovation, Bogers and Lhuillery (2011) assert that the successful absorption of external knowledge related to product and process innovations requires higher absorptive capacity at the functional level (e.g. manufacturing, marketing and R&D) in organisations. The authors argue that product and process innovations demand a different level of absorptive capacities in each of the functional departments to absorb knowledge from a variety of external partners. For instance, they found that the manufacturing function plays a significant role in absorbing competitors' knowledge for process innovations, while it also plays an important role in absorbing supplier knowledge for product innovations. Moreover, R&D is crucial for absorbing product knowledge from public research organisations, and marketing helps in absorbing customer knowledge for both product and process innovations. Similarly, Krzeminska and Eckert (2015) investigated the complementarity effect of internal and external R&D on the innovation success of product and process innovations. They found a significant level of complementarities between internal and external R&D for product innovations; however, they found limited evidence of complementarities between internal and external R&D for process innovations. These studies suggest that the external sources of knowledge for product innovations significantly differ from those of process innovations.

In addition to the difference in external sources of knowledge, product and process innovations differ in their learning strategies and degree of novelty. While firms tend to pursue exploratory learning strategies to develop product innovations, they adopt exploitative learning strategies to develop process innovations (Un and Asakawa, 2015). The differences in the learning strategies can influence the collaboration behaviour of firms such that exploratory-focused innovations may require firms to collaborate with partners who can offer diversified knowledge (Van Wijk et al., 2008), whereas exploitation-focused innovations may require collaborations with partners who have a more similar knowledge base (Dooley et al., 2015). Moreover, product innovations tend to achieve radical improvement, which again requires diversity in sources of knowledge and ideas (Fitjar and Rodríguez-Pose, 2011; Jansen et al., 2006). On the contrary, process innovations tend to focus on incremental innovations by improving existing ways of doing things (Jansen et al., 2006; Westerlund and Rajala, 2010).

Some authors investigate the creation of product and process innovations from the perspective of leadership and management practices. Leadership is assumed to be a kind of dynamic capability (knowledge acquisition capability) that could affect the product and process innovations outcome. In the context of China, Chang et al. (2015) found that transformational-charismatic leadership improved product innovations, and transactional leadership showed a stronger impact on process innovations. In a similar vein, Haneda and Ito (2018) hypothesised that organisational and human resource management practices of an R&D department could influence the success of product and process innovations. Having a board member with an R&D

background positively affects product innovations, while the interdivisional cooperation among R&D centres significantly influences both the product and process innovations.

Finally, product and process innovations affect different areas within the organisations (Gopalakrishnan and Damanpour, 1997). For instance, product innovations are developed separately in a quasi-independent unit such as a dedicated R&D department (Un and Asakawa, 2015), while process innovations are more interrelated with other systems of the organisation (Gopalakrishnan et al., 1999). Moreover, these two innovations differ based on the nature and characteristics of knowledge (Gopalakrishnan and Bierly, 2001; Un and Asakawa, 2015). The knowledge required for the development of process innovation is relatively more tacit, complex and systematic, whereas the knowledge required to develop new product innovations is relatively simple, codified and autonomous (e.g. Casanueva et al., 2013; Gopalakrishnan et al., 1999; Hatch and Mowery, 1998; Krzeminska and Eckert, 2015; Terjesen and Patel, 2017; Wong et al., 2008). Owing to these significant differences, the collaboration activities of firms for introducing product innovations may differ from that of process innovations.

The predominant argument is that the coordination of complex and tacit knowledge is difficult (Van Wijk et al., 2011). Therefore, firms tend to collaborate with partners having similar attributes to ease knowledge transfer. On the contrary, simple and explicit knowledge transfer may not require collaboration with partners with similar attributes because simple knowledge is easy to transfer (Dhanaraj et al., 2004). However, prior research suggests that firms are heterogeneous agents which differ significantly from one another in their capabilities (Nelson and Winter, 1982). These differences in the capabilities result in asymmetric interactions among firms (Boschma and Ter Wal, 2007; Giuliani, 2007; Morrison and Rabellotti, 2009). For instance, firms with a higher level of absorptive and innovative capacity may not be willing to collaborate with firms which have a lower level of absorptive capacity (Morrison, 2008). The role of absorptive and innovative capacity may become more crucial when the knowledge is complex and tacit. As Balland and Rigby (2017) argued, the diffusion and production of complex and tacit knowledge is very difficult, requiring similarity among the knowledge bases of the collaborating partners.

Therefore, in this paper, I set out to investigate the network formation of the product and process innovations with a view to understanding whether and how the antecedents of these two innovation networks differ from each other. Notably, I examine the individual, dyadic and structural level drivers of product and process innovation networks. At an individual level, I investigate the role of absorptive capacity and innovative capacity, which may distinctively influence the likelihood of collaborations for product and process innovations. Similarly, at a structural level, I study endogenous network mechanisms such as popularity, activity, reciprocity and transitivity, and examine their role in the network formation of product and process innovations. Finally, at dyadic level, I investigate the role of business relations in influencing the formation of product and process innovation networks. The next section presents the research hypothesis of this study.

4.3 Research hypothesis

4.3.1 Absorptive capacity as a determinant of product and process innovation networks

Absorptive capacity is defined as "the ability to recognise the value of new information, assimilate it and apply it to commercial ends", which is essential for the successful transfer and acquisition of knowledge (Cohen and Levinthal, 1990, p.128). The tendency of firms to establish knowledge linkages with other firms depends on the similarity in their knowledge bases (e.g. Lane and Lubatkin, 1998). The higher the difference among the knowledge base of a firms and its external knowledge source, the more difficult it is for the focal firm to successfully acquire and absorb external knowledge. In order to understand new external knowledge, firms must possess prior basic knowledge (i.e. show a basic understanding of the traditions and techniques in a specific field) related to the new knowledge. For instance, in the textile industry, dyeing and printing of textile products requires basic knowledge of chemistry. Without understanding chemistry, an individual may not be able to understand the processing of dyes and chemicals.

In addition to the prior basic knowledge, the characteristics of new knowledge play a vital role in its transfer and circulation. The literature on organisational learning and the notion of absorptive capacity suggests that the characteristics of knowledge (e.g. tacit/explicit) affects its acquisition and transfer among cooperating firms (Lane et al., 2006; Wang and Han, 2011). The three predominant properties of knowledge that make its transfer difficult are tacitness, complexity and the content of knowledge (Lane et al., 2006, p.846).

Tacit knowledge is embedded within the complex routines and interactions of the firms, and therefore it is 'sticky' in nature (von Hippel, 1988). This property of knowledge creates hurdles in its transfer and makes it difficult to move from one place to another. Similarly, complex knowledge is also difficult to transfer because it is integrated into several sub-systems (Saviotti, 2011). These subsystems are based on a variety of knowledge contents and therefore demand higher absorptive capacity to understand the linkages between the different knowledge contents, which creates difficulty for an individual or a firm in the absorption of new external knowledge (Garund and Nayyar, 1994). On the contrary, simple, explicit and autonomous knowledge is relatively easy to transfer and absorb because it is available in the codified form in manuals and code books (Dhanaraj et al., 2004), thus requiring minimum absorptive capacity by firms (Lane et al., 2006).

Since product innovation knowledge is relatively simple, explicit and autonomous (Gopalakrishnan et al., 1999; Gopalakrishnan and Bierly, 2001; Wong et al., 2008), the firms with a minimum level of absorptive capacity may also be able to understand the knowledge of higher absorptive capacity firms. Particularly in this situation, the likelihood of interactions between higher absorptive capacity firms and others will be higher for product innovation-related advice.

In contrast, the knowledge characteristics of process innovations are relatively more complex, tacit and systemic (Gopalakrishnan et al., 1999; Gopalakrishnan and Bierly, 2001; Un and Asakawa, 2015; Wong et al., 2008). The production and diffusion of complex knowledge is difficult (Balland and Rigby, 2017), therefore firms may need a higher absorptive capacity to absorb such complex knowledge. However, if the absorptive capacity of firms is below the minimum threshold, they may not be able to understand the complex knowledge of other higher absorptive capacity firms; thus, linkage formation between high and low absorptive is less likely to occur. In turn, firms with a higher absorptive capacity may receive relatively fewer requests for technical advice for process innovations.

Regarding the advice-seeking behaviour of advanced absorptive capacity firms, these firms are unlikely to seek advice from other low absorptive capacity firms because they do not see value in the advice of low absorptive capacity firms (Giuliani, 2007; Molina-Morales et al., 2015). I believe that this relationship may be true for both the product and process innovations related advice and thus expect an insignificant coefficient of absorptive capacity for out-going ties.

From the above discussion, I expect that whilst absorptive capacity is vital innovation-related knowledge, the association between higher absorptive capacity and network formation be positive only for incoming ties, and not for outgoing ties. I expect this to be true for both the product and process innovations. Hence, I formulate the following hypothesis:

H1a. Absorptive capacity is positively associated with the formation of product and process innovation networks; however, this relationship will be positive and significant only when these firms act as advice givers (high in-degree centrality).

H1b. The magnitude of absorptive capacity is expected to be relatively higher for the product innovations network than the process innovations network.

4.3.2 Innovative capacity as a determinant of product and process innovation networks

External knowledge plays a vital role in the innovation process of firms. Firms tend to acquire knowledge from a variety of external sources. While absorptive capacity is essential to value, understand, assimilate and utilise the new external knowledge (Cohen and Levinthal, 1990), firms need to have enough innovative capacity to develop innovations for the final market (Khilji et al., 2006). Lichtenthaler and Lichtenthaler (2009, 1321) define innovative capacity as “a firm’s ability to exploit knowledge internally”. However, firms need combinative capabilities to internally exploit new knowledge coming from external sources, which means that the firms need to have a prior stock of knowledge and resources that can be combined with the new knowledge to develop innovations (Kogut and Zander, 1992). Indeed, firms’ internal resources and external linkages both jointly determine whether firms have enough capability or not.

The external linkages or knowledge networks of firms (especially clustered firms) are crucial for their innovative capacity. Boschma and Ter Wal (2007) assert that when firms interact only with local sources of external knowledge and not with non-local sources of knowledge, their learning ability may weaken up to the extent that they lose innovative capacity. In turn, firms which have connectivity with extra-regional partners may have higher innovative capacity than locally connected firms that may have a lower innovative capacity. The difference in innovative capacity can affect the future inter-firm collaborations among firms, such that interactions among higher innovative capacity firms are less likely to happen because they may be afraid of ideas being appropriated (Morrison, 2008). Hence, I expect that innovative firms will avoid establishing relationships with other local firms for both the product and process innovations to sustain their competitive advantage over others. Moreover, in the context of a mature industrial cluster[11] - where the technology path

[11] This study is based on a traditional textile cluster, where the product market is same for all firms. Large clients often place their orders to several innovative producer firms but keep it hidden from the other local producers to negotiate better prices. The technical specifications for new products and

becomes increasingly focused and technological innovations, are less significant with a decline in heterogeneity among firms' capabilities (Menzel and Fornahl, 2009), it is riskier to share knowledge and information about both product and process innovations because competitors can imitate products and processes with relatively less effort. Thus, innovative firms are likely to avoid collaboration with other firms in the cluster. Thus, I submit the following hypothesis:

H2. *Firms with higher innovative capacity are less likely to establish technical advice linkages with other clustered firms for both product and process innovations.*

4.3.3 Network structural effects as a determinant of product and process innovation networks

In addition to individual attributes of actors, network structural interdependencies play an important role in the formation of networks (Rank et al., 2010). The literature acknowledges various types of network configurations that emerge as a result of everyday interactions among firms as well as individuals (Boschma et al., 2015; Robin et al., 2012). However, I do not yet know whether the structural patterns of interpersonal relationships in product innovations networks differ from that of process innovation networks. Thus, in this paper, I focus on four relevant network configurations for detailed investigation: popularity, activity, reciprocity, and transitivity.

The most studied network configuration is the degree distribution of nodes. Network studies widely acknowledge that real networks often follow power law distribution (Giuliani and Bell, 2005), which means that some nodes are more popular than other nodes (Boschma et al., 2015). This popularity effect is very similar to the concept of preferential attachment, which refers to the attractiveness of central actors and expects that actors with many connections

compliance standards for relevant processes are provided to the local producers. In this context, innovative firms avoid external collaborations because this is the only way to protect information leakage to other innovative firms. If the information about running product orders are leaked then other innovative firms will try to approach the client and break the deal in their favour (Golra, 2016).

are more likely to establish new connections over time (Glückler, 2007; Ozman, 2009). Several studies have investigated the role of preferential attachment in network formation (Balland et al., 2016; Boschma et al., 2015; Giuliani, 2013). Popular actors are often the leading firms that are more central in a network, and therefore other unconnected firms may prefer to connect to these leading firms.

Similar to popularity effect, the literature highlights the importance of activity effect, which is the tendency of seeking advice from many other actors (Rank et al., 2010; Robins, 2009). Several studies have shown that firms and individuals tend to seek advice from many other actors (Balland et al., 2016; Brennecke and Rank, 2017; Robin et al., 2012). For instance, Balland et al. (2016) found a positive and significant effect of activity in the business and technical advice networks. The authors observed that some actors tend to be very active in asking advice in the toy cluster in Spain. In contrast, Balland et al. (2016) observed that preferential attachment is an essential phenomenon in shaping the dynamics of business networks while it plays a minor role in the formation of technical networks. In another study on patent citation in the biotech sector, Boschma et al., (2015) found a significant effect of preferential attachment in the inter-firm knowledge spillovers.

To understand whether popularity and activity effects exhibit similar patterns in product and process innovation networks, I distinguish product and process innovations by knowledge characteristics. On the one hand, process knowledge is relatively more complex, systemic and tacit (Gopalakrishnan et al., 1999; Wong et al., 2008). The production and diffusion of complex knowledge is very difficult (Balland and Rigby, 2017), which means only a few leading and capable firms may be able to produce it and subsequently diffuse it among the other local firms. In doing so, these leading firms may emerge as the primary source of process knowledge for other local firms. Consequently, they can become popular in the local cluster. Rank et al. (2010) aver that individuals and organisations may look to those for advice who are popular and trusted by several others. On the other hand, product knowledge is relatively explicit, autonomous and simple (Gopalakrishnan et al., 1999; Wong et al., 2008). Therefore, it is relatively easy to acquire product knowledge from any partner. Due to this reason, it is less likely that any specific firm will emerge as a primary source of knowledge. Thus, I do not expect any significant popularity effect in the product innovations network:

> *H3a. The popularity effect is positively associated with process innovations network, and there will be no significant association between the popularity effect and the product innovations network.*
>
> *H3b. The activity effect is positively associated with process innovations network, and there will be no significant association between activity effect and the product innovations network.*

Although popularity and activity are crucial, reciprocity has been considered as a fundamental force behind network formation at dyadic level (Lee and Lee, 2015; Rank et al., 2010). It is a property of a directed or asymmetric network. In this configuration, the presence of a tie between firm *i* to *j* encourages firm *j* to form a reciprocal tie with actor *i*. In this manner, the two firms can exchange useful resources and knowledge by mutual exchange. By no means is it universal or deterministic. However, there is a strong tendency towards reciprocity (Robin et al., 2012). Reciprocal ties are also found to be frequent among competing firms (von Hipple, 1987). Moreover, in the cluster context, reciprocity has been found to play an essential role in the circulation of knowledge among clustered firms (Giuliani, 2013). Scholars have found reciprocity to be a more important factor in technical/knowledge networks than business/information networks (Balland et al., 2016; Morrison and Rabellotti, 2009). In my study I focus on the technical aspects of product and process innovations; therefore, I expect reciprocity to play a positive and significant role in the formation of both innovation networks. Hence, I submit the following hypothesis:

H4. Reciprocity significantly promotes the formation of product and process innovation networks.

The relationship between dyads is not independent of the influence of other members of the network (Rank et al., 2010). A node in a network may or may not be connected indirectly to several other nodes of that network. When I consider a set of three nodes it is likely that various structural patterns of triads emerge (Lee and Lee, 2015). One of the most common patterns is a triangle, which occurs when two actors form a new tie owing to their existing tie with a third common network partner (e.g., A→C and B→C, then A→B or B→A) (Molina-Morales et al., 2015). In other words, ‘friends of friends are likely to become friends’.

Network closure or transitivity is an essential structural mechanism that frequently occurs in the network relational data (Robins et al., 2012). There are different theories in the literature on the importance of network closure ‘triangles’ and non-closure ‘structural holes’ (e.g. Granovetter, 1983; Burt, 1992). Research has widely mentioned the advantage and disadvantage of both. In cluster studies, this phenomenon is often associated with the cohesion effect, which means that *firms tend to connect in stable, closed and dense social structures* (Giuliani, 2013).

In the context of this study where firms under investigation belong to a specific geographical cluster, the network closure is likely to occur in innovation-related knowledge exchange for both product and process innovation. However, the transitivity effect is likely to be slightly higher for the process innovation network. It is because process innovations have an internal focus and are primarily efficiency driven (Utterback and Abernathy, 1975). Process innovations are introduced into the organisation’s production and operations systems to produce a product or render a service (Damanpour and Gopalakrishnan, 2001). In order to improve the production efficiencies, these firms closely observe other clustered firms to learn any new or improved efficient method developed by any other clustered firm. This action by firms generates a transitivity effect in the process innovation network. Finally process knowledge is complex in nature and scholars argue that the sharing of complex information requires embedded ties (Powell and Grodal, 2006). Owing to the complexity of process knowledge, I expect a high transitivity effect in the process innovations network because high transitivity leads to high embeddedness among partners.

By contrast, product innovations tend to be driven by the customer with a focus on the final market, and these are often introduced to meet an external user need (Damanpour and Gopalakrishnan, 2001). Thus, firms require diversified knowledge to develop product innovations. In the context of this study, the primary customers are global buyers who operate from outside the cluster boundaries, i.e. in the global market, and therefore sharing of new product development ideas mainly comes from customers and not from other clustered firms. Even though new ideas come from the customers, cluster firms tend to share product-related technical advice with one another. Owing to frequent advice sharing among cluster firms, I expect to observe a significant transitivity effect in the product innovations network:

H5. Transitivity significantly promotes the formation of product and process innovation networks. The magnitude of transitivity is likely to be higher for process innovation network than product innovation network

4.3.4 Business relations as a determinant of product and process innovation networks

Cluster firms share both technical and business-related knowledge. Giuliani (2007) argued that the structure of a business and technical network differ from each other and that the firms establish technical relations on a more selective and pervasive basis, whereas business relations are more common, unstructured and uniform among firms. Balland et al. (2016) also showed that the dynamics of business networks and technical networks differ to a large extent. Firms prefer to collaborate with cognitively proximate partners for only technical advice linkages; however social embeddedness drives the formation of both the technical and business relations. Morrison and Rabellotti (2009) studied information networks in an Italian wine cluster and supported the findings of Giuliani (2007). These authors also found differences in the structural properties of business and information networks. They argue that the structural properties differ because of the nature of the two networks.

Similarly, Kim and Lui (2015) found that market network is more positively related to organisational innovation and the institutional network is more positively related to product innovation. They maintained that product and organisational innovations have different network antecedents. The underlying motives and incentives to pursue product innovations are different from those of organisational innovations. Therefore it is essential to study these two innovation types differently.

Moreover, the motives and incentives to pursue product innovations are different from process innovations (Antonelli and Fassio, 2016) and the knowledge required to produce product innovations is different from process innovations (Gopalakrishnan et al., 1999); the importance and role of business relations may be different for both innovations. Product innovations require diversified ideas from diverse partners, whereas process innovations require more specific knowledge from specialised firms (Callois, 2008), and business relations provide access to a variety of external sources and, particularly in industrial clusters, business relations are unstructured and pervasive (Giuliani, 2007). Therefore, I can assume that business relations are more important for product innovation than process innovations:

H6. The business network is positively related with both product and process innovation networks. However, the magnitude will be higher for the product innovations network.

4.4 Research context and method of data analysis

4.4.1 Context of the current study

The empirical context of my study is the Lahore textile cluster in Pakistan, which is the second most populous city in Pakistan, with a total population of around 11.07 Million in 2018 (Demographia, 2018) and which accounts for around 10% of the total textile and clothing firms in the country (PBS, 2013). The city is a hub of many industries including textile and clothing. The textile Industry is considered the backbone of the economy of Pakistan. It contributes to around 54% of the country's total exports, employs 40% of the industrial workforce and also accounts for 8% of the total GDP (Pakistan Textile Policy, 2014-19). The industry is scattered across the country in the form of several clusters. The most prominent textile industrial clusters are located in the cities of Lahore; Faisalabad; Sheikhupura and Sialkot in the province of Punjab; and Karachi, Sukkur and Hyderabad in the province of Sindh.

Lahore is one of the most important cities in Pakistan. According to a recent study on the effects of agglomeration on socio-economic outcomes in Punjab-Pakistan, Lahore has the second highest road density among the 29 clusters in Punjab with a significant amount of industrial agglomeration in the cluster (Azhar and Adil, 2019). According to the census of manufacturing industries conducted by the Pakistan Bureau of Statistics in 2005-06 (PBS, 2013), there are 170 textile and apparel firms in Lahore[12]. These firms are involved in almost all stages of the textile value chain, i.e., yarn manufacturing; knitted and woven fabric manufacturing; dyeing, printing and finishing of fabric; apparel and made-ups (Hamid et al., 2014). They are located mainly in four different locations in Lahore, i.e. Raiwind-Manga Mandi, Bhai Peru, Ferozepur Road and Defence Road. Azhar and Adil (2019) provide empirical evidence that shows a significant industrial agglomeration in Lahore and other parts of Punjab province. Although the Lahore cluster has shown considerable agglomeration of textile firms, it has not received attention from scholars. Most

[12] In our data, the minimum number of employees reported by firms is 500 and the maximum number is 7000. On average, each firm employs approximately 1834 workers.

studies have highlighted the importance of the Faisalabad textile cluster (Islam, 2006), but Lahore textile cluster, despite its contribution to the local economy, has yet to be studied. Hamid and Nabi (2014) have asserted that the government of Punjab has recently designated a special place to promote the garment industry in Lahore.

I believe that the Lahore textile cluster provides an interesting case to investigate the social interactions among firms and particularly the network formation of product and process innovations because there is a strong culture of cooperation and support that exists among cluster firms in Pakistan (Islam, 2006). In the next section, I present the data collection method.

4.4.2 Data Collection

In the present study, I collected firm-level primary data. In the preliminary stage, I conducted a pilot study during October and November 2015. I conducted seven face-to-face semi-structured interviews with the senior managers (affiliated to the divisions of production, research and product development) of four local textile manufacturing firms. I sought information on firms' attributes (to construct explanatory variables and control variables) and their informal interactions with the other local firms in the industrial cluster (to construct network variables).

After the pilot study, I collected the final data during the second and third quarter of 2016. I collected information from 73 large-scale manufacturing firms in the Lahore textile industrial cluster in Pakistan. I decided to administer the questionnaire via face-to-face interviews in order to minimise the data handling errors. Moreover, this strategy was adopted because firm-level informal relational data (social network data) is generally not available from secondary data sources (Balland et al., 2016; Boschma and Ter Wal, 2007; Giuliani and Bell, 2005). I interviewed the top level technical personnel who were responsible for the development of product and process innovations. I selected these people because during the pilot study I were told that technical directors, general managers or R&D heads are the most important and unique sources of information. Huber (2013) also suggested that scholars can obtain critical information by exploring the personal knowledge networks (social networks) of senior managers.

In addition to the survey, I also collected secondary data from other sources, such as firms' websites, government databases and trade associations' websites. These sources provided missing information and also corroborated the already collected data on explanatory and control variables. Another purpose of this exercise of data collection was to triangulate the data obtained via face to face interviews. Following Giuliani and Bell (2005), and Boschma and Ter Wal (2007), I used roster recall methodology (Wasserman and Fraust, 1994) to collect my relational data. I also mixed roster recall methodology with the free-recall approach and allowed the firms to add the names of other advice seekers and givers, which were not in the roster.

In my study, I collected data from all the textile firms located in the four municipalities in the city of Lahore. I downloaded the members' directory of the All Pakistan Textile Mill Association (APTMA). According to the list, 84 large textile firms are operating in the city of Lahore. During the pilot study, the managers told us that several firms had stopped their operations due to the severe energy crisis. Therefore, I surveyed only those firms that were active at the time of data collection, and my final list consists of 73 firms in total.

4.4.3 Measures

4.4.3.1 Network variables for product and process innovation

A social network analysis software package UCINET 6 was used to analyse the relational data (Borgatti, Everett & Freeman, 2002). My study sought information on two directed networks, i.e. product and process innovation networks.

Product & process innovations network/matrix

Since my primary purpose is to estimate the likelihood that two actors will form an advice linkage for product and process development, my first dependent variable is an n*n (73*73) socio-matrix for 'product innovations network', which is a dichotomous variable and indicates whether firm 'i' or 'j' mention the other as a source of technological knowledge for new products development. Similarly, my second dependent variable is a 73*73 socio-matrix for process innovations network, which is also a dichotomous variable and indicates whether firm 'i' or 'j' mention the other as a source of technological knowledge for new process development. It takes the value 0 when there is no link and the value 1 when there is a link. The questions sought information for directed graph. I followed Giuliani and Bell (2005) and Molina-Morales et al. (2015), and established a directed network. I asked the following questions to gather relational data about product and process innovations advice sharing:

When you need technical advice on product development/innovation, to which of the local firms mentioned in the roster do you turn?

When you need technical advice on process improvement/innovation, to which of the local firms mentioned in the roster do you turn?

4.4.3.2 Non-structural variables (node level and dyad level effects)

Absorptive capacity

In this study, absorptive capacity is one of the critical variables. I measured absorptive capacity by running a principal component analysis of firms' human capital, R&D efforts and internationalisation efforts (See Appendix A for details). Scholars have extensively studied this variable and measured it as the capacity of organisations to absorb external knowledge produced by others. There is, as such, no single measure of absorptive capacity in the literature. This construct is often associated with the research and development efforts of a firm and measured in a variety of ways; for instance, the presence of skilled employees (Molina-Morales et al., 2015), R&D spending (Boari et al., 2017; Cohen and Levinthal, 1990; Presutti et al., 2017);

R&D intensity (Tsai, 2001); using a likert scale (Liao and Yu, 2013); the number of patents produced in a specific time period (Boschma et al., 2015); and applying principal component analysis (PCA) to the R&D efforts and skilled human resource (Boschma and Ter Wal, 2007; Giuliani and Bell, 2005; Giuliani, 2007; Giuliani, 2013).

Innovative capacity

In traditional industries such as textiles, global buyers or customers who are at the end of the value chain mainly drive the innovation process by governing the producers (Gereffi et al., 2005). Innovative capacity is associated with the demands of the end market, and firms need to produce innovations according to the requirements of the end user (Cohen and Levinthal, 1990). In the context of the current study, the firms can do that by achieving compliance with the global standards, because strict compliance standards set by the leading global brands are one of the significant challenges for local firms (SMEDA Pakistan, 2018). These global buyers demand compliance on various standards such as quality, safety, environment and social standards, which is difficult for the low capacity local firms to achieve. I measure this by the number of international certifications secured by the local firms such as ISO 9001-2000 quality management system.

Business relational network

The business network is a dyadic variable measured by the memberships of firms in the local trade associations. In total, I observed 15 trade association operating in the textile industry in Pakistan. Some of them provide support to specific industry divisions (e.g. Pakistan Readymade Garments Manufacturing Association). However, others provide general support with the industry (e.g. Lahore Chamber of Commerce and Industries). I created a network matrix based on the co-memberships of the firms in these associations and tested whether co-memberships in trade associations increases the likelihood of collaborations in the product innovation and process innovation network. The importance of business associations in economic development is widely acknowledged (e.g. Houghton et al., 2009; McCormick et al. 2008).

4.4.3.3 Structural variables and network level effects

The structural variables included in my model are described below;

Density (Edges)

The interpretation of this variable is similar to the constant term in regression analysis. It is the general tendency of an organisation to form a tie with other organisations. Density should always be included in an ERGM model to control for the general likelihood of tie formation (Hunter et al., 2008). In other words, the simplest model only contains edges, which is the null model in ERGM. I can measure it by calculating the out-degree of firms:

$$Di = \sum_j x_{ij} \qquad \textit{Eq.1}$$

Reciprocity (Mutuality)

The reciprocity is an important effect in the directed networks. It is based on the principle of mutual exchange of (e.g.) resources and specifies the general tendency of an actor to return the favour to others. Reciprocity is the number of reciprocal ties of an actor '*i*' in the network (Boschma et al. 2015):

$$R_i = \sum_j x_{ij} x_{ji} \qquad \textit{Eq.2}$$

GWD (Geometric weighted degrees)

The GWD was proposed to deal with the decreasing degree distribution in the observed network (Harris, 2014) and to capture the alternating *k*-star in the network (Hunter, 2007; Hunter et al., 2008). A weighing parameter is multiplied by the frequency associated with each value of a degree and then sums up all the values by using the following equation:

$$u(y;\alpha) = e^{\alpha} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\alpha})^{i} D_i(y)\} \qquad \textit{Eq.3}$$

In equation 3, $u(y;\alpha)$ is defined as the geometrically weighted degree for the observed network y. The degree is represented by *i* and $D_i(y)$ represents the nodes in the network with degree *i* (Hunter 2007, Harris 2014). The alpha 'α' is the decay parameter which is estimated. The multiplier term $\{1 - (1 - e^{-\alpha})^{i}$ is used to weigh the degrees and α is the degree weighing parameter. The value of the statistics depends up on the value of the decay parameter and the degree distribution of the observed network (Harris 2014). The size GWD statistics is affected by two factors i.e. a number of high-degree nodes *i* and the value of decay parameter α. This ensures that the nodes with a high-degree contributes more to the statistics.

In the current study, I focus on directed networks. Therefore both in-degree and out-degree terms for GWD was included in the model. It was done to capture the popularity and activity effect in the network (Snijders et al., 2006).

GWINDegree (Popularity effect)

Gwindegree measures the in-degree distribution of actors and captures the popularity effect, which means that some actors are more popular than the rest of the actors in the network and are therefore more likely to receive requests from other actors. A positive parameter estimate suggests skewness in the in-degree distribution (Robin, 2012) and reflects the attractiveness of an actor that already receives many requests for tie formation (Boschma et al., 2015). By contrast, a negative estimate indicates homogeneity in the in-degree distribution. This effect can be calculated by the following equation (Snijders et al., 2006):

$$\sum_i x_i y_{+i} \qquad \textit{Eq.4}$$

For geometrically weighted in-degrees, the following equation is proposed by Hunter (2007) and Hunter et al. (2008):

$$u_{in}(y;\alpha) = e^{\alpha} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\alpha})^{+i} D_i(y)_{in}\} \qquad \textit{Eq.5}$$

In equation 5, all symbols are the same as equation 3, except $u_{in}(y;\alpha)$, *+i,* and $D_i(y)_{in}$, which represents values for the geometrically weighted in-degrees.

GWOUTDegree (Activity effect)

Gwoutdegree measures the out-degree distribution of actors. The positive parameter estimate indicates heterogeneity in the out-degree distribution with some nodes showing a higher number of outgoing ties. The following equation can calculate the activity effect, and a positive result increases the correlation between the out-degree distribution and the covariate (Snijders et al., 2006):

$$\sum_i x_i y_{i+} \qquad \textit{Eq.6}$$

For geometrically weighted out-degrees, the following equation can be used (Hunter 2007, Hunter et al. 2008):

$$u_{out}(y;\alpha) = e^{\alpha} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\alpha})^{i+} D_i(y)_{out}\} \qquad \textit{Eq.7}$$

In equation 7, all symbols are the same as equation 3, except the terms $u_{out}(y;\alpha)$, *i+,* and $D_i(y)_{out}$, which represent values for the geometrically weighted out-degrees:

Transitivity (Network closure)

Transitivity refers to local clustering of actors, and it leads to triadic network closure. I can write the general mathematical expression for transitivity as $T_i = \sum_{j,h} x_{ij} x_{ih} x_{jh}$. A positive parameter estimate suggests closure effect in the network such that actor *j* and *h* are likely to establish tie if both are already connected to actor *i* in the above equation (Boschma et al. 2015). Snijders et al. (2006) and Hunter et al. (2008) suggest geometrically weighted terms to measure the transitivity effect in an ERGM model.

GWESP (Geometrically Weighted Edge-wise Shared Partner)

The term GWESP was developed to capture the alternating *k*-triangle, i.e. transitivity patterns in the network, and it indicates the cohesion effect. I measure it by the following equation suggested by Hunter et al. (2008):

$$v(y;\alpha) = e^{\alpha} \sum_{i=1}^{n-2} \{1 - (1 - e^{-\alpha})^{i} ESP_i(y)\} \qquad \textit{Eq.8}$$

In equation 8, $v(y;\alpha)$ is defined as the geometrically weighted edge-wise shared partner and $ESP_i(y)$ represents the number of edges that have exactly *i* shared partners (Hunter et al., 2008). The rest of the equation is consistent with equation 3.

The symbol terms *u, v, w, in* equation 3 and 9, coincide with the alternating *k*-star, *k*-triangle and *k*-two-path statistics as given in Snijders et al. (2006).

4.4.3.4 Control variables

In addition to the firm level attributes and network structural variables, I controlled for several variables at the attribute and dyadic levels.

First I controlled for four proximity dimensions at dyadic level i.e. *Geographic Proximity* (measured as inverse of distance between firms in kilometres), *Cognitive Proximity* (measured by similarity in the technological bases of firms), *Organisational Proximity* (measured as similarity in ownership structure), and *Social Proximity* (measured by similarity in past experience). Golra et al. (2018) found a significant influence of these four proximity dimensions on the formation of product and process innovation networks.

In the context of my study, I measured the uniform homophily effect (Goodreau, 2007) among the firms at the university level, i.e. asking managers about the name of their professional degree awarding institute. If the two managers belong to the *same university,* then it is likely that they support each other. In my sample, most of the managers are the graduates of the national textile university.

I also controlled for the cooperation among the managers due to their *professional qualification,* i.e. engineering plus business graduates, only engineers and non-engineers. I aim to control whether managers having different qualifications have different levels of relational intensity in terms of tie formation. To measure this variable, I used the nodal-factor effect. “Given a particular level of a particular factor (i.e., categorical variable), the nodal factor effect counts the total number of endpoints with that level for each edge in the network” (Hunter et al., 2008, p.250).

I controlled for the size of firms and measured it by the number of employees. I estimated the parameter by using the nodal covariate effect (Hunter et al., 2008). I also controlled for *the export performance* of firms. The firms with higher export performance are likely to establish more linkages, therefore I controlled for this effect. I measured export performance by categorical variable. I provided four options to the firms in the questionnaire regarding their level of exports, i.e. 1 (0 to 25%), 2 (25 to 50%), 3 (50 to 75%) and 4 (75 to 100%). I calculated the nodefactor effect with reference category being the least exporter firms. I controlled for the size of firms and measure it by the number of employees. I estimated the parameter by using the node covariate effect.

Finally, I control for the term GWDSP *(Geometrically Weighted Dyad-wise Shared Partner)*, which is developed to capture the alternating *k*-towpath statistics, i.e. multiple connectivities in the network. A positive parameter estimate indicates non-closure and the presence of structural holes. The following equation measures GWDSP:

$$w(y;\alpha) = e^{\alpha} \sum_{i=1}^{n-2} \{1 - (1 - e^{-\alpha})^{i} DSP_i(y)\} \qquad Eq.9$$

In equation 9, $w(y;\alpha)$ is defined as the geometrically weighted dyad-wise shared partner and $DSP_i(y)$ represents the number of dyads that have exactly *i* common partners (Hunter et al. 2008; Goodreau, 2007). The rest of the equation is consistent with equation 3.

4.5 Estimation model

This study uses cross-sectional social network data. Different network-based models can be used to test the hypothesis in social network studies. The most commonly used techniques are multiple regression quadratic assignment procedures (MRQAP) (Dekker et al. 2007), and exponential random graph models (ERGM) (e.g. Snijders et al., 2006 and Robins et al. 2012). In order to test the hypothesis in the present study, I apply the Exponential Random Graph Model (ERGM) for two main reasons. First, ERGM models allow the modelling of node level data as well as relational and network structural properties altogether which is not (directly) possible in the MRQAP model (Broekel and Hartog, 2013). In order to incorporate node level data in the MRQAP model, the original data in vector format require conversion to matrix format (Borgatti et al. 2013), which eventually requires a different type of hypothesis. Similarly, network level data cannot be incorporated into MRQAP models (Broekel and Hartog, 2013). Second, I aim to estimate the probability of tie formation based on specific covariates and ERGMs are appropriate to predict the probability of a tie between two actors, conditional on all the rest of the ties (Harris 2014). One way to express basic ERGM model is:

$$P(Y = y) = \frac{\exp\{\theta' g(y)\}}{k(\theta)} \qquad \textit{Eq.10}$$

In equation 10, Y is a network generated by an exponential random graph and $P(Y = y)$ is the probability that Y is identical to the observed network y. $g(y)$ is a vector of model statistics (e.g. covariates) and θ represents coefficients for the modelled terms at the node level, dyadic level and structural level. The network statistics of these terms or determinants obtain a value of 1 if a corresponding configuration is observed and otherwise 0. $k(\theta)$ is a normalising constant to ensure that probability distribution summed up to 1. The above equation can also be written as:

$$logit(P\left(Y_{ij} = 1 \middle| Y^c\right) = \theta' \Delta\{g(y)\}_{ij} \qquad \textit{Eq.11}$$

In equation 11, Y_{ij} is a random variable for the state of actor pair in Y; Y^c is the other dyads in the network, or in other words the rest of the network; $\Delta(g(y))_{ij}$ is the change statistics for each model term and records the change in $g(y)$ when Y_{ij} toggled (Butts et al., 2014).

The aim of solving the above equations is to find parameters for the configurations that maximise the likelihood of obtaining the simulated random network identical to the observed network (Broekel and Hartog, 2013). This fitting is done with Monte Carlo Markov Chain maximum likelihood estimation that is an algorithm based on a simulation of graphs (Snijders et al., 2006; Hunter et al., 2008). This procedure can be performed by using advanced simulation software. The positive parameter estimates suggest that there are more than a random chance that a configuration occurs in the network, whereas negative parameter estimate indicates that a configuration has a less than random chance to occur in the network (Broekel and Hartog, 2013; Robins, 2012). The current study run the ERGM model using package 'statnet' (Hunter et al. 2008) in R software.

These models are increasingly being used in innovation-related network studies in a variety of industrial settings (e.g. Broekel and Hartog, 2013; Molina-Morales et al., 2015; Capone and Lazzeretti, 2015) because standard regression models are not suitable for network-based studies. These standard models are based on the assumption of independence, and in relational (dyadic) data this assumption is not met. Therefore, standard tools of inference are problematic (Krackhardt, 1987). ERGM presents a solution to this problem of dyadic dependence of observations and assumes that two ties are conditionally dependent on other possible dyads in the network (Snijders et al., 2006). Indeed, standard regression models based on the assumption of the independence of observations do not take into account structural patterns of the network as explanatory variables may lead to a biased estimation.

I applied ERGM to predict the occurrence of configuration in the observed network. The observed network is a dependent variable in my model, which was predicted by node levels, dyad levels and structural levels covariates such as the absorptive capacity of firms (node covariate) and business relations (dyad covariate), and edges, gwdegree, gwdsp, gwesp (structural variables). The three terms gwdegree, gwdsp, gwesp require calculating a parametric value alpha. To do that I followed the procedure defined by Hunter et al. (2008) and tried different values starting from 0. The next section will present the results of my analysis

4.6 Results and discussion

This section presents the results of the paper and discusses the impact of different variables on the formation and dynamics of the product and process innovation network.

The descriptive statistics are presented in Tables 4-1 to 4-3 followed by ERGM model statistics in Table 4-4 and Table 4-5 for process innovation networks and product innovation networks respectively. Additionally, figures 4-1 to 4-3 present the graphical representation of network graphs and network goodness of fit statistics for the process innovations network, while figures 4-4 to 4-6 present the graphical representation of network graphs and network goodness of fit statistics for the product innovations network (Please see Appendix B).

Table 4-1 Descriptive Statistics of Explanatory Variables

Variable	Measurement	Type of data	SD	MIN	MAX
Firm Absorptive Capacity	PCA Index	Continuous	1	-1.83	1.55
Firm Innovation Capacity	No. of int'l certifications	Continuous	1.19	0	4.24
Exports performance	Export level of firm	Categorical	1.22	1	4
Firm Size	Log of no of employees	Continuous	0.312	2.6	3.85
Manager's university affiliation	Top manager's affiliation	Dichotomous	0.49	0	1
Manager qualification	Degree level of manager	Categorical	0.53	1	3
Geographic proximity	Inverse log-distance in km	Continuous	0.422	0	1.822
Cognitive proximity	Cosine Index	Continuous	0.388	0	1
Social proximity (employment)	Shared past employment	Dichotomous	0.082	0	1
Organisational proximity	Same Parent Company	Dichotomous	0.136	0	1
Business network	Same Trade Memberships	Dichotomous	0.497	0	1

In total, I ran eight models. Model 1-4 in Table 4-4 presents ERGM results for the process innovations network, while Model 5-8 in Table 4-5 presents the ERGM results for the product innovations network. I estimated ERGM for the product and process network in four steps each. In the first step, I only included the edge parameter. The second step is the baseline model in which the firm level attributes were added followed by dyadic covariates in the third step (intermediary model) and finally network structural effects were incorporated in the final step. This process is in line with previous studies (Molina Morales et al., 2015). Goodreau (2007) suggests that researchers should perform ERGM analysis in steps because in this manner, the influence of endogenous network forces on the attribute and dyadic variables can be assessed in a precise manner. Following Hunter et al. (2008), I also checked the goodness of fit statistics of my model by comparing the observed network with the set of simulate networks.

Table 4-2 Descriptive Statistics of Network Variables

Description of Variable	Std. Dev	No. of Ties	Avg. Degree	Density
Product Network	0.196	206	2.88	0.039
Process Network	0.216	259	3.55	0.049
Business Network	0.477	1848	25.31	0.352

Table 4-3 Technology profile and organisational structure of firms

Characteristics	*Number of firms (%), (n=73)*
Organisational structure	
Independent Textile Firm (one value chain active)	15 (21%)
Part of Textile Group (several value chains in textile industry)	18 (25%)
Multi-sector group (textile value chains + other industries)	40 (55%)
Technology Profile (PSIC Code)	
Spinning (1311)	37 (26%)
Weaving (1312)	21 (14%)
Textile Processing (1313)	36 (25%)
Knitting (1391)	8 (6%)
Home Textile Made-ups (1392)	7 (5%)
Embroidery work (1399)	13 (9%)
Apparel & Garments excl. Knitted (1410)	18 (12%)
Knitted Apparel & Garments (1430)	5 (3%)

Absorptive capacity

My results largely support my theoretical predictions. In the first hypothesis, H1a, I predict that absorptive capacity tends to play a positive and significant role in the formation of both the product and process innovation networks. I also expect that firms with higher absorptive capacity are likely to receive requests from many other firms for technical advice. Simultaneously, these higher absorptive capacity firms may not seek advice from the other local firms in the cluster because they do not see any value in the advice of firms with a lower level of absorptive capacity. As shown in Table 4-5, the estimate for absorptive capacity (in-degree) is positive and significant for the product innovations network (Est. = 0.61, p-value <0.001). Similarly, Table 3-4 demonstrates a positive and significant effect of the process innovations network (Est. = 0.42, p-value <0.001). These findings suggest that firms with higher absorptive capacity are likely to receive advice requests from many other firms for solving technical problems related with both the product and process innovations. Conversely, these higher absorptive capacity firms do not seek advice from the other local firms in the cluster for both process innovations (Est. = -0.03, p>0.1) and product innovations (Est. = 0.07, p>0.1), as shown in Tables 4-4 and 4-5 respectively. Thus, these results confirm my first hypothesis H1a. These results are partially in line with Giuliani and Bell's (2005) study, which found a positive and significant association between absorptive capacity and both in/out degree centrality. However, I find positive and significant relationship with incoming ties only. The possible reason for these findings is that leading firms do not see any value in the advice of other local firms who have a lower level of absorptive capacities. Therefore, in order to absorb new knowledge, these leading firms prefer to collaborate with extra-cluster sources of knowledge instead of collaborating with other local firms. This is because innovative knowledge is often available from outside cluster boundaries through global pipelines rather than from the other local firms (Boschma and Ter Wal, 2007; Giuliani, 2007; Morrison et al., 2013).

Table 4-4 Process Innovation Network: ERGM Model Estimation

Estimate (se)	1 Null model	2 Baseline model	3 Intermediate model	4 Final model
Edges (constant)	-2.96*** (0.06)	-8.08*** (1.15)	-8.88*** (1.30)	-8.08*** (1.41)
Absorptive Capacity (In-degree)		0.35** (0.10)	0.43*** (0.13)	0.42** (0.13)
Absorptive Capacity (Out-degree)		0.07 (0.10)	-0.14 (0.12)	-.03 (0.13)
Innovation Capacity		-0.12+ (0.07)	-0.23** (0.08)	-0.27** (0.08)
Size (No of employees)		0.41* (0.16)	-0.07 (0.18)	0.02 (0.18)
Graduated from National Textile Univ.		0.60*** (0.16)	0.46* (0.18)	0.35* (0.18)
Qualification Level-1 (Non-degree)	Reference	Reference	Reference	Reference
Qualification Level-2 (Eng degree)		1.15*** (0.27)	1.39*** (0.29)	1.45*** (0.32)
Qualification Level-3 (Engg. + Business)		1.10*** (0.26)	1.43*** (0.29)	1.49*** (0.32)
Export Level-1 (<25%)	Reference	Reference	Reference	Reference
Export Level-2 (>25% up to 50%)		0.31+ (0.17)	0.70*** (0.18)	0.49** (0.18)
Export Level-3 (>50% up to 75%)		0.11 (0.19)	0.61*** (0.21)	0.47* (0.21)
Export Level-4 (>75% up to 100%)		0.49* (0.20)	1.10*** (0.22)	0.83*** (0.23)
Geographic Proximity			0.36* (0.17)	0.24 (0.15)
Cognitive Proximity			3.85*** (0.25)	2.09*** (0.24)
Social Proximity			1.97*** (0.39)	2.00*** (0.41)
Organisational Proximity			2.44*** (0.29)	1.75*** (0.25)
Business network			0.52** (0.17)	0.46** (0.16)
Mutual (*Reciprocity)*				0.85** (0.27)
Gwidegree (0.7) - *Popularity*				1.13* (0.44)
Gwodegree(0.7) - *Activity*				1.56*** (0.47)
Gwdsp.fixed.0.25 (*Multi-connectivity)*				-0.21*** (0.03)
Gwesp.fixed.0.25 (*Transitivity)*				0.94*** (0.13)
Log Likelihood	-1032 (df=1)	-975.61 (df=11)	-714.77 (df=16)	-657.96 (df=21)
AIC	2066	1973	1462	1358
BIC	2073	1951	1567	1496
MCMC diagnostics – Joint P-value (Lower = worse)				0.82

*Significance codes: P<0.001*** ; P< 0.01**; P< 0.05* ; P<0.1 +*

Table 4-5 Product Innovation Network: ERGM Model Estimation

Estimate (se)	5	6	7	8
	Null model	Baseline model	Intermediate model	Final model
Edges (constant)	-3.199*** (0.07)	-9.03*** (1.22)	-10.04*** (1.36)	-8.12*** (0.1.35)
Absorptive Capacity (In-degree)		0.62*** (0.12)	0.72*** (0.14)	0.61*** (0.14)
Absorptive Capacity (Out-degree)		0.25* (0.12)	0.07 (0.14)	0.07 (0.14)
Innovation Capacity		-0.18* (0.08)	-0.30*** (0.09)	-0.26** (0.08)
Size (No of employees)		0.77*** (0.17)	0.44* (0.19)	0.31+ (0.18)
Graduated from National Textile Univ.		0.66*** (0.18)	0.46* (0.20)	0.34+ (0.19)
Qualification Level-1 (Non-degree)		Reference	Reference	Reference
Qualification Level-2 (Engg degree)		0.62* (0.28)	0.78** (0.29)	0.63* (0.28)
Qualification Level-3 (Engg. + Business)		0.70** (0.27)	0.94** (0.29)	0.76** (0.27)
Export Level-1 (<25%)		Reference	Reference	Reference
Export Level-2 (>25% up to 50%)		0.27 (0.19)	0.49* (0.20)	0.34+ (0.18)
Export Level-3 (>50% up to 75%)		0.07 (0.21)	0.45+ (0.23)	0.33 (0.20)
Export Level-4 (>75% up to 100%)		-0.04 (0.24)	0.33 (0.25)	0.18 (0.23)
Geographic Proximity			0.72*** (0.18)	0.58*** (0.16)
Cognitive Proximity			2.97*** (0.24)	1.96*** (0.23)
Social Proximity			1.75*** (0.40)	1.72*** (0.41)
Organisational Proximity			1.94*** (0.28)	1.30*** (0.25)
Business network			0.59** (0.19)	0.50** (0.17)
Mutual (*Reciprocity)*				1.37*** (0.29)
Gwidegree (0.7) - *Popularity*				-0.07 (0.40)
Gwodegree(0.7) - *Activity*				0.53 (0.42)
Gwdsp.fixed.0.25 (*Multi-connectivity)*				-0.09* (0.04)
Gwesp.fixed.0.25 (*Transitivity)*				0.58*** (0.13)
Log Likelihood	-869.19 (df=1)	-812.36 (df=11)	-647.70 (df=16)	-619.89 (df=21)
AIC	1740	1647	1327	1282
BIC	1747	1719	1432	1420
MCMC diagnostics – Joint P-value (Lower = worse)				0.96

*Significance codes: P<0.001*** ; P< 0.01**; P< 0.05* ; P<0.1* +

In *H1b*, I hypothesise that the magnitude of the absorptive capacity coefficient will be higher for the product innovations network than the process innovations network. I can confirm my theoretical predictions because the coefficient of absorptive capacity for the product innovations network is higher for product innovations network (Est. = 0.61, p-value <0.001) than the process innovations network (Est. = 0.42, p-value <0.001), as shown in Tables 4-4 and 3-5. The reason is that process knowledge is relatively more complex and tacit, which is difficult to produce (Balland and Rigby, 2017), therefore firms with lower absorptive capacity are less likely to understand the complex and tacit knowledge that resides with the leading firms. Hence, the odds of observing a tie among higher absorptive capacity firms for product innovations [exp (0.61) = 1.84] is 32% higher than the odds of observing a tie among higher absorptive capacity firms for process innovations [exp (0.42) = 1.52]. Therefore, I can corroborate my hypothesis H1b.

Innovation capacity

In the second hypothesis, *H2*, I examine the role of innovative capacity in network formation. I expect that innovative firms are less likely to interact with other cluster firms. Since I mentioned elsewhere that in the context of my study, the product market is the same for all innovative firms (i.e. leading brands in global/international market), the leading innovative firms tend to hide their innovative knowledge from the other clustered firms. Thus, these innovative firms are less likely to establish knowledge linkages with other firms irrespective of their innovative capacity and the type of innovation. My results support hypothesis 2, and I found a negative and significant effect for both the product (Est. = -0.26, p-value <0.01) and process (Est. = -0.27, p-value <0.01) innovation networks, as shown in Tables 4-4 & 4-5. This result suggest innovative firms avoid knowledge sharing with other cluster firms regardless of the type of innovation. A possible reason might be that, in the context of the current study, both the product and process innovations may be equally important to gain competitive advantage, thus, highly innovative firms tend to protect their knowledge of product and process innovations from spilling over to other firms in the cluster.

On the one hand, these findings are consistent with other studies on clusters and industrial districts which argue that in clusters, the access to knowledge is restricted only to a few actors that can offer some useful knowledge and information in return (Giuliani, 2007; Morrison and Rabellotti, 2009). Indeed, leading firms in industrial clusters may not be willing to share knowledge with both the small firms as well as other leaders because small firms may not reciprocate useful knowledge whereas other leaders may appropriate innovative ideas (Morrison, 2008). On the other hand, my findings contradict those of Ahuja's (2000) study which demonstrates that firms with high innovative outputs are more likely to form alliances. A possible reason for these contrasting results might be that whilst Ahuja (2000) investigated the linkage activities among leading firms in the global chemical industry, I studied linkage formation in a mature industrial cluster in Pakistan.

Structural effects

Regarding the structrual interdependencies, first, I tested for the popularity and activity effects in my model. While popularity (Est. = -.07, $p>0.1$) and activity (Est. = 0.54, $p>0.1$) effects are not significant for the product innovations network, as shown in Table 4-5. Both of these effects are positive and significant *(popularity est. = 1.13, $p<0.05$ & activity est. = 1.56, $p<0.001$)* for the process innovations network, as shown in Table 4-4. These results support my hypothesis *H3a* and *H3b* in which I propose that popularity and activity will be significant for the process innovations network only. The finding that suggests that popularity is positive and significant for the process innovations network is in line with those previous studies that have shown a positive and significant effect of popularity (preferential attachment). For instance, Boschma et al. (2015) found a positive and significant coefficient for preferential attachment in patent citation in the bio-tech sector. Similarly, significant results regarding activity effect in the process innovation networks are consistent with Balland et al. (2016) who found positive and significant effects of activity on both business and technical networks. On the contrary, my insignificant results on popularity and product innovations network are consistent with previous research (Lee and Lee, 2015) which did not find a significant relationship between popularity and creative ties.

Second, I tested for the role of reciprocity and found a positive and significant effect of reciprocity on both the product innovations network (Est. = 1.37, *$p<0.001$)* and process innovation networks (Est. = 0.85, *$p<0.001$),* as shown in Table 4-4 & 4-5. Hence, I can confirm my hypothesis *H4.* However, the coefficient is higher for the product innovations network. This result suggests that the circulation of product knowledge particularly requires stronger relationships and a higher level of trustworthiness because competitors can reverse engineer the competing products reasonably quickly if they have access to critical information (Laursen and Salter 2014); therefore, I argue that there are high appropriability concerns associated with product innovations (i.e. protecting product knowledge to gain appropriable returns on innovating efforts). Firms tend to share product knowledge only with other highly trusted partners on high mutual grounds in order to avoid the risk of opportunistic behaviour.

My findings are in line with earlier studies that suggest that mutual cooperation among clustered firms is a common phenomenon, which demands high stability and trustworthiness to facilitate knowledge sharing. Morrison and Rabellotti (2009) showed that the percentage of reciprocal ties in the knowledge network is much higher than the percentage in information network. In a more recent study, Brennecke and Rank (2017) found that the odds of reciprocity among inventors are more than twenty times the odds of no reciprocation, which means an inventor is twenty times more likely to return an advice/favour to the other inventor who has provided advice.

Regarding the transitivity effect, it is positive and significant for both product and process innovation networks (Est. = 0.58 and Est. = 0.94 respectively and significant at *$p<0.001$*); however higher for process innovation network which shows that network closure is more often observed in the process innovation network than the product innovation network. These results confirm my hypothesis *H5*. Although I did not propose any hypothesis for multi-connectivity, I included it in my final models to control its effect. I find a negative and significant effect of multi-connectivity for both the process innovations network (Est. = -0.21 and significant at $p<0.001$) and the product innovations network (Est. = -0.09 and significant at $p<0.05$). These results suggest that structural holes are less likely to be found in both networks, which means firms are embedded in dense social relations.

Business relations

Finally, I proposed that the business relations are more important for the product innovations network than the process innovations network. The coefficient for the business network- measured through trade memberships, is positive and significant for both the product and process innovations network. Moreover, the coefficient is higher for the former (Est. = 0.50 and significant at $p<0.001$) than the latter (Est. = 0.46 and significant at $p<0.01$), as shown in Tables 4-4 & 4-5. These findings show that business relations play a more critical role in providing diversified information to the collaborating partners which ultimately helps to develop new products and to improve new processes. This finding is in line with Houghton et al. (2009) who argue that a trade association membership is an important source of knowledge for firms because it offers socialisation opportunities to firms' executive to exchange ideas with one another about new products and technologies. Hence, my results corroborate hypothesis *H6.*

4.7 Conclusion

In this paper, I study some predominant determinants of the formation and dynamics of product and process innovation networks. The key contribution of paper lies in the geography of innovation and network studies literature. The findings of this paper suggest that the dynamics of the formation of product and process innovation networks are inherently different from each other particularly when it comes to the endogenous network properties. I found a significant and positive association between the variable of absorptive capacity and both networks. This effect is significant for incoming ties which implies that higher absorptive capacity firms are less likely to seek advice from other clustered firms both for product and process innovations.

I also investigated the association between innovation capacity and network formation. I found a significant negative effect on both product and process innovation networks. The magnitude of the innovative capacity effect is almost the same on the product and process innovation network. This result suggests that firms with higher innovative capacity are unlikely to connect to other firms.

The absorptive capacity and innovative capacity are the attribute variables in my study and explain the phenomena of network formation through social selection mechanism. In addition to attribute variables, I studied the role of structural interdependencies among the product and process innovation networks. I found a significant presence of reciprocity effect in both the process of product and process innovation networks. The transitivity effect is higher for the process innovation network than the product innovation network. The possible reason might be that the primary customers are operating outside the cluster boundaries, i.e. in the global market, and therefore sharing of new product development ideas mainly comes from customers and not from other clustered firms. By contrast, to improve the production efficiencies, the local firms may closely observe the processes of other clustered firms in order to learn any new or improved method developed locally. The close observation of one another generates a transitivity effect in the process innovation network.

My results regarding the role of business relations are particularly interesting. I find a positive and significant role of business relations in the formation of product and process innovation networks. These findings are important because prior research on industrial clusters argue that business relations are pervasive and they may not play a crucial role in the innovation process (e.g. Giuliani and Bell, 2005; Giuliani, 2007; Morrison, 2008). In contrast, my study suggests that business relations among firms established through memberships in trade associations play a significant role in promoting technical advice related interactions for both product and process innovations.

Chapter 5 Influence of firms' network position on their innovation outcome in a mature industrial cluster

5.1 Introduction

Innovation is primarily a collaborative effort (Chesbrough, 2003; Laursen and Salter, 2006; Leenders and Dolfsma, 2016; von Hippel 1988, 2005) and is a result of complex social interactions among actors (Laursen et al., 2014). Whether operationalised as informal networks (Bell and Zaheer 2007, Semrau and Werner, 2014; Uzzi, 1997) or formal networks (Mazzola et al. 2015, 2016; Ozmel et al., 2013; Whittington et al., 2009), these relationships remain crucial for innovation and complex problem solving (Gargiulo et al., 2009; Laursen et al., 2012), as well as, sustained competitive advantage (Dyer and Singh, 1998).

Much research in this field has focused on the concept of structural and relational embeddedness (Cowan, Jonard and Zimmermann, 2007). On the one hand, scholars argue that the performance of a firm depends on its structural position in the network (Balland et al., 2016; Batjargal, 2007). Such that a firm with a prominent position in the network tends to have access to crucial resources and knowledge which consequently affect its innovation (Ahuja, 2000; Burt, 2004; Tan et al., 2015; Zaheer and Bell, 2005). On the other hand, several studies emphasise that, although a firm's structural position plays an important role, the strength and quality of its inter-firm relationships also affects the innovation output of the firm (Batjargal, 2003; Moran, 2005). The past two decades have witnessed numerous empirical contributions to this embeddedness debate. However, there is a considerable research gap in our understanding of the role of the firm's structural and relational embeddedness on its innovation output in directed networks. Thus, this paper aims to fill this research gap and examines the structural and relational properties of a firm in directed networks and their impact on a firm's innovation output.

The literature on innovation networks provides ample empirical evidence about the impact of network structural properties on innovation (Ahuja et al., 2012; Boschma et al., 2014). However, there is a need for further evidence on directed networks in which relationships are often asymmetrically distributed

(Gargiulo et al., 2009). Hansen and Mattes (2018) argue that the interactions among firms that engage in collaborative innovation and learning processes are seldom entirely reciprocal. Consequently, it leads to an uneven distribution of information and knowledge among collaborating partners (Giuliani, 2007; Morrison and Rabellotti, 2009). Up to this point, only a few studies have highlighted the importance of the direction of ties and distinguished between the role of an acquirer and a provider of information (Phelphs et al., 2012; Reagans and McEvily, 2003). These studies pointed out that benefits associated with a dominant structural position in a network are contingent upon the direction of the information flow, such that a prominent structural position may or may not positively contribute to the innovation outcome of firms per se; instead, it depends on the role (e.g. advice seekers or givers) these firms play in the knowledge transfer process. In this respect, Phelps et al. (2012) noted that the successful transfer of information and knowledge is not limited to the efforts of a source but also require the receiver's efforts to acquire and absorb it.

Nevertheless, the knowledge transfer is typically beneficial for the receiver and can be costly for the provider (Reagans and McEvily, 2003). In a similar vein, an important study was carried out by Gargiulo and colleagues (Gargiulo et al., 2009) who have investigated the impact of network closure on the financial outcome of bankers. They found that network closure increases the performance of bankers when they act as information acquirers, and that it decreases performance when bankers act as information providers in an informal network.

From a different perspective, Soltis et al. (2013) study the impact of advice-seeking and advice-giving ties on employees' turnover intentions in a life sciences organisation. The authors argue that employees' turnover intentions are influenced by their predominant role as advice-givers or advice-seekers. Employees who are being highly sought out for advice (advice-givers) are more likely to quit the organisation than those who frequently seek out advice (advice-seekers) from others because advice-givers see themselves as over-burned and under-rewarded (Soltis et al., 2013). These studies indicate that the role a firm plays in directed networks can have consequences for its innovation output. Studying the firm's advice-giving and advice-receiving behaviour separately will enhance our understanding of the differentiating effects of network positioning. Since it may be possible that a firm may have a prominent position in an advice-giving role, and simultaneously, it may not hold a predominant position in the advice-receiving role (or vice versa). In such a case, there could be significant implications for research and development managers.

As discussed, little is known about the influence of firms' structural positions on innovation in the advice-seeking and advice-giving roles, as well as about the quality and strength of the relationship between collaborating partners. Therefore, my study aims to fill this research gap and poses the question: *whether and how do firms' embeddedness in an advice-seeking role (being active) and advice-giving role (being popular) impact their innovation outcome in the context of a mature industrial cluster?*

I study innovation networks in a mature textile industrial cluster in Lahore, Pakistan. Using social network analysis (SNA) and ordinary least square (OLS) regression method, I studied the impact of in-degree and out-degree centrality on the innovation output of the firms. My findings suggest that a predominant role in advice-giving and advice-receiving have an opposing impact on a firm's innovation output. Moreover, absorptive capacity mediates the relationship between advice-giving ties and innovation.

My study contributes to the literature in three ways. First, I contribute to the network and embeddedness literature by explicitly incorporating the direction of a tie in the analysis and show that the structural embeddedness in advice-seeking and advice-giving has different consequences on the innovation outcome. Second, I contribute to the learning and innovation literature and demonstrate that in a mature industrial cluster the direct effect of structural embeddedness on innovation is mediated by absorptive capacity, which implies that merely network centrality is not enough for innovation. Instead, higher knowledge absorption capability is essential to develop innovations. Third, I respond to the recent calls from network scholars to include network studies from a variety of contexts, particularly emerging countries' perspectives. Network scholars highlight that the way networks operate in the context of developing countries remains empirically under-explored (Zhang et al., 2019). These studies emphasised that network studies should examine the conditioning effect of context (Batjargal, 2007; Kraft and Baush, 2018). Thus, I believe my study is timely as well as crucial.

The next section presents the literature review followed by a research hypothesis. Subsequently, I present the methodology section. The results are presented in the penultimate section followed by the discussion and conclusion of the paper at the end.

5.2 Literature Review

The position firms occupy in networks can have significant consequences for their ability to exchange information with other members, which in turn should affect their performance. Research shows that some network positions are advantageous while others prevent the members from accessing and benefitting from a range of opportunities and resources that impact outcome (Nahapiet, 2009). Numerous studies have shed light on the benefits and detriments of having a prominent structural position in the network (Burt, 1992; Coleman, 1988; Iurkov et al., 2018; Kraft and Baush, 2018; Leenders and Dolfsma, 2016; Shijaku et al., 2018; Ruef, 2002; Tan et al., 2015; Whittington et al., 2009; Zaheer and Bell, 2005; Zhang et al., 2019). Some studies have also shown that firms are embedded in multiple relations and therefore acquire multiple positions in different networks at the same time, which has consequences for innovation outcome (Boschma and Ter Wal, 2007; Giuliani, 2007, Mazzola et al. 2015, 2016; Ozmel et al., 2013; Wang et al., 2014). Recent studies have highlighted that these network positions are not static, and firms shift positions over the period, and this dynamic positioning influences innovation (Gilsing et al., 2016; Mazzola et al., 2018). A central thesis of all the above studies is that the innovation output of firms is contingent upon their embedded positions in the networks. Whether the networks are static, dynamic, single or multiple, structural embeddedness is imperative.

Regarding the role of structural embeddedness in innovation promotion, there are two main competing arguments about what type of network structure is beneficial for innovation (Batjargal, 2007). On the one hand, coherent and dense connections encourage cooperative behaviour, which promotes trust and minimises opportunistic behaviour (Coleman, 1988). On the other hand, sparse networks rich in structural holes provide access to diversified information, which contributes to innovation (Burt, 2004). This debate focuses on the analysis of network structural properties and investigates, how network positions, such as centrality and structural-hole, influence the innovation and economic outcome of actors (Boschma et al., 2014). Research shows that firms who connect to many other actors, or in other words who hold a central place in a network, have access to (and control over) more information than the other non-central firms. This central position, in turn, eases knowledge transfer (Reagans and McEvily, 2003), affects innovative performance (Ahuja 2000; Bell, 2005; Ho and Chiu, 2013; Powel et al., 1996), and improves the economic activity of firms (Boschma et al., 2014). Similarly, firms who span structural-holes in a network may have access to more diversified information than other firms (Ahuja, 2000; Batjargal 2007; Burt, 2004; Zaheer and Bell, 2005), which play an essential role in enhancing creativity.

In addition to structural embeddedness which is by far the most studied concept in social network research, relational embeddedness is also critical. Relational embeddedness focuses on the quality of relationships and involves overlapping interpersonal ties often referred to as strong ties (Granovetter, 1973). Relational embeddedness also comprises of the weak relations that play an essential role in spreading information because they tend to connect otherwise disconnected actors (Ruef, 2002). Notably, to understand the influence of network contacts on innovation, it is not the structure of network contacts that is all that matters; the quality and strength of relationships matter too (Moran, 2005). In a study on the product and sales managers of a Fortune

100 pharmaceutical firm, Moran (2005) presents evidence that the relational embeddedness among managers plays a stronger role in explaining the innovation-related performance, whereas structural embeddedness plays a stronger role in sales-related performance. Batjargal (2003) also demonstrated that weak ties have a positive and significant impact on both the revenue growth and profit margin of Russian entrepreneurs.

More recently, some scholars suggest that the role of context is also crucial in explaining the influence of network structure on innovation. For instance, in a recent meta-analytic study, Kraft and Bausch (2018) show that institutional context plays an essential role in moderating the influence of network structure on innovation. The authors suggest that cohesive networks are more useful for innovation in a weak institutional setting as well as collectivistic cultures, whereas diverse networks are effective under strong institutional setting as well as individualistic cultures. Similarly, Gilsing et al., (2016) demonstrate that firms' network positioning varies along the path of technological change and exhibits non-linear progression through the phases of birth, growth and maturity of a technology. This study shows that the impact of structural position changes with the change in the context of technological change. These studies suggest that the context, in which firms are embedded, plays an essential role in influencing the effect of network structural properties.

Some other studies suggest that in order to remain competitive in the industry over a longer period, firms often shift their positions in the network structure. Ahuja et al. (2012) refer to this mechanism as the agency micro-foundation of the network dynamics, which implies that a firm chooses its network partners by establishing or dissolving connections deliberately. A firm adopts this approach to obtain maximum benefits out of its network contacts. In this way, a firm knows its position in the network, and it can change positions with the change in opportunities. This dynamic positioning consequently affects the outcome of a firm. Mazzola et al. (2018) showed that the firms who adopt dynamic positioning, that is shifting from a central to structural holes positions (and vice versa) over time are more likely to develop new products. These studies suggest that a firm's inter-organisational strategy drives its choice of network position. Thus, it is the firm's own decision whether it wants to form or dissolve a network link.

Finally, several other scholars suggest that examining the conditioning effect of context and the use of dynamic lens is important, but networks are not uni-plex, which means firms are often connected via multiple relations (Mazzola et al., 2015; Mazzola et al., 2016; Ram and Rosenkopf, 2014; Shipilov et al., 2014). Hence, researches should study the influence of overlapping connections on the innovation output. For instance, Mazzola et al. (2016) found that a prominent position in an interlocking directorate can improve the influence of the inter-firm network on new product development. Wang et al. (2014) also show that centrality and structural holes in the knowledge and collaboration networks have a different impact on firm-level exploratory innovation. Structural holes in a collaboration network enhance exploratory innovation while structural holes in the knowledge network decrease exploratory innovation. Soltis et al. (2013) showed that advice ties and work-related ties are often overlapping with each other in a way that an actor seeks advice from the same person with whom she is required to work with. The authors found that voluntary advice-seeking ties (ties outside workflow network) negatively affect turnover intentions, while advice-seeking ties (intertwined with workflow ties) do not have a significant effect on employees' turnover intentions. The authors found opposite effects in advice-giving ties, which shows that studying multiplex relations is essential, but the direction of the tie plays a crucial part in explaining the outcome.

I argue that all the above-cited studies have made a remarkable contribution in the network literature, and while there is a considerable research gap in our understanding of the impact of firms' embeddedness in the directed networks, I argue that it is crucial to include the direction of the link in the analysis especially in the informal interactions because informal networks in regional clusters arise from reciprocal linkages among co-located firms. These inter-firm linkages may not necessarily exhibit symmetry. Notably, in advice exchange relationships, some firms may receive more advice requests from others than they could seek out from others (or vice versa). In turn, this imbalance of information exchange can have a differentiated effect on firms' performance.

5.3 Research hypothesis

5.3.1 Relational embeddedness and innovation

Relational embeddedness defines the strength and quality of the relationship among firms (Moran, 2005). Studies have measured relational embeddedness through strong and weak ties (Granovetter, 1973) and trustworthiness in the relationships or networks (Moran, 2005). Strong ties (such as friends and family) are beneficial because they entail high trust and cooperative behaviour among partners, and reduce opportunistic behaviour (Coleman, 1988). Contrarily, strong ties limit access to diversified information and therefore create redundancy in information and resources which may negatively affect the outcome. Uzzi (1996) relates this phenomenon of redundancy with the notion of "over-embeddedness" and highlights the detrimental effects of strong ties. Alternatively, Hansen (1999) argues that strong ties play an essential role in the transfer of highly complex knowledge because complex knowledge requires close coordination and trust which is not possible without having healthy and strong relationships.

On the one hand, weak ties are considered a source of non-redundant and diversified information. Several studies have shown that weak ties positively contribute to achieving a competitive advantage because they connect otherwise disconnected actors (Burt, 1992). There are merits and demerits associated with both strong and weak ties. In a mature industrial cluster, the norms are well-established, and most of the actors are embedded in strong relations, which is good to control opportunistic behaviour. Anyone who breaks the norms has to face sanctions. Therefore, firms may be highly cooperative with each other and this cooperative behavior can positively affect firms' innovative outcome.

On the other hand, weak ties in a mature industrial cluster may not bring more benefits to the clustered firms because most of the information available in the cluster is redundant. In a mature cluster, the technology path becomes increasingly focused and technological innovations are less significant with a decline in heterogeneity among firms' capabilities (Menzel and Fornahl, 2009); therfore, it is more risky to share knowledge and information with others with whom there does not exist a strong and trustworthy relationship. However, due to the same product market and customers (global buyers), trustworthiness becomes even more critical. Hence I propose that:

H1: Strong ties will positively affect the innovation output of firms

H2: Weak ties will negatively affect the innovation outcome of firms

5.3.2 Structural Embeddedness and Innovation

A plethora of studies has shown that structural embeddedness of a firm in a network influences its innovation. Network size (or degree centrality), structural holes and density are often used as parameters to measure the structural embeddedness of firms (Batjargal, 2003). However, previous studies have presented competing arguments. Some scholars argue that sparse networks rich in structural holes are beneficial for the innovation outcome of firms because sparse networks provide access to diversified information that helps in creating innovative solutions (Burt, 1992).

On the contrary, others argue that dense connections among collaborating firms promote trust and minimise opportunistic behaviour (Coleman, 1988). Several studies have contributed to the debate on these two competing arguments and scholars have found both the positive and negative impact of structural embeddedness on innovation. For instance, Tsai (2001) found a direct relationship between a unit's central position in an inter-organisational network and its business unit innovation. In a similar vein, Bell (2005) found that centrality in a managerial network increases firm innovativeness, while centrality in an institutional network does not show any relationship with innovativeness. The simple logic is that a central position provides access to a variety of resources, which contributes to innovation. In some cases, scholars have not found any relationship between centrality and innovation (Batjargal, 2003; 2007).

The studies are not limited to the relationship between centrality and innovation; they have also tested at large the theses of the structural hole and density and innovation. For instance, Ahuja (2000) found that structural holes exert both a positive and negative influence on innovation, while Zaheer and Bell (2005) found a positive and significant effect on firm performance. Zaheer and Soda (2009) showed that the bigger the increase in the number of structural holes in the network of the focal team, the higher the performance of the team. Some scholars have argued that the presence and absence of structural holes in a network can be relevant, but the institutional environment plays a crucial role. For instance, Vasudeva, Zaheer, and Hernandez (2013) showed that structural holes have a more positive impact on innovation when the brokering firm or its network partners are located in countries with higher levels of corporatism. The authors emphasised that although structural holes play an important role in explaining innovation, the actual impact can only be understood by incorporating the institutional environment in the analysis because institutional corporatism influences the collaborative behaviour of partners. Zhang et al. (2019) also supported this idea and avered that the impact of structural holes and centrality is contingent upon the context. They found a significant difference in the influence of structural holes in the Western and Chinese context. They showed in a meta-analytic study that although centrality and the structural holes are both positively related to performance, the impact of structural holes is not significant in the Chinse context. Likewise, Kraft and Baush (2018) showed that the institutional environment significantly moderates the impact of bonding and bridging on innovation. Their study revealed that cohesive networks are more beneficial in a weak regulatory and political environmental context and collectivistic cultures, while sparse networks are beneficial in a robust institutional context and individualistic culture. Therefore, industrial managers can cope with the challenges of diverse institutional settings by adjusting their network position according to the institutional context.

Over the past twenty years, scholars have produced a considerable amount of publications studying the direct, indirect and moderating relationships between structural embeddedness and innovation. However, I find that very few studies have incorporated the direction of a tie in the analysis. I argue that the impact of network positions is contingent upon the direction of a tie, that is, the role which a firm plays in the collaboration process, mainly when the collaboration is associated with a valuable resource and knowledge. For instance, if the firm is on the provider end of the tie, then the impact of its network position on the innovation might have a different impact when the firm takes on the role of the acquirer of information. There are a few studies that have attempted to understand the relationship between network position and outcome. For instance, Soltis et al. (2013) found that centrality in the advice-giving network has a positive relationship with employee intention to leave. This study shows that those employees that are highly sought out for advice by others feel over-burned, and thus showed a higher intension to leave. On the contrary, employees who seek regular advice from others were found to have a lower intention to leave. However, this latter finding showed an insignificant relationship. In another study, Gargiulo et al. (2009) revealed that network closure increases the performance of bankers when they act as information acquirers and decreases performance when bankers act as information providers in an informal network.

Overall, these findings suggest that an acquirer role is beneficial and the provider role is harmful. However, I argue that these results will be reversed if I study the relationship between advice-giving and advice-seeking in a mature industrial environment/context where firms are often embedded in dense connections. For instance, in a mature industrial cluster the information available to actors can be highly redundant. In turn, firms who seek out advice from many other actors are likely to end up with a large amount of redundant information. Tan et al. (2015) showed that the positive impact of centrality on innovation can turn negative in high density networks. In other words, the higher the number of direct advice-seeking relations maintained by a focal firm, the more the cost of the knowledge search and network maintenance (Hansen, 2002). Consequently, the cost of maintaining network ties exceeds the benefits they can provide. I further argue that this scenario may also be true when a focal firm is connected to other powerful actors in the network.

On the contrary, although advice-giving ties require time helping others, they may provide benefits to advice givers because they may be able to seek better favour in return to the advice they have given to advice-seekers. Based on the above arguments, I propose the following hypotheses:

H3: Advice-giving ties are positively associated with the innovation output of firms in a mature industrial cluster

H4: Advice-seeking ties are negatively associated with the innovation output of firms in a mature industrial cluster

5.3.3 The mediating role of absorptive capacity between centrality and innovation

In this paper, I are interested in understanding the mediating role of absorptive capacity between innovation and network position. The absorptive capacity is the ability of firms "to recognise the value of new information, assimilate it and apply it to commercial ends" (Cohen and Levinthal, 1990, p.128). Moreover, it is essential for successful knowledge transfer and acquisition. Absorptive capacity has been found to have a positive impact on firms' innovation outcome (Tsai 2001, Lane et al. 2006). Some scholars have tested the moderation effect of absorptive capacity. For instance, Tsai (2001) investigated the relationship between network position and absorptive capacity. The author showed a positive interaction effect between absorptive capacity and central position in the network.

Nevertheless, in this study, I expect that the absorptive capacity of a firm will mediate the impact of network position on innovation. Several studies have shown that firms with higher absorptive capacity are likely to attract several other firms to establish knowledge and advice related linkages because clustered firms tend to seek advice from higher absorptive capacity firms (Balland et al. 2016; Giuliani and Bell, 2005; Giuliani, 2007).

Consequently, firms with higher absorptive capacity are likely to have a central position in the advice-giving network. However, it is not necessary that all firms with higher absorptive capacity also maintain a central position in a network. Boschma and Ter Wal (2007) found no relationship between higher absorptive capacity firms and their position in the local network.

Similarly, Giuliani and Bell (2005) found that some of the higher absorptive firms preferred to hold a peripheral position instead of a central position. The authors referred to those firms as 'external stars' and argued that the star firms were more technologically advanced than the other clustered firms; therefore, they remained disconnected from the local network. Particularly in the case of a mature industrial cluster, the information available to clustered firms is highly redundant. Therefore, firms may prefer to hold a peripheral position instead of a central position. Another argument is that when new information is not available from inside the clusters, firms with higher absorptive capacity may look for information outside the cluster boundaries and connect to global pipelines to acquire non-redundant information and knowledge (Morrison et al., 2013). Finally, research suggest that network position is not enough to be innovative and rather firms need capabilities to take advantage of the position (Boari et al., 2017). Indeed, the benefits of structural position is contingent upon focal firms' capabilities (Zaheer and Bell, 2005). These studies suggest that firm-level capabilities are a predominant factor in acquiring a beneficial network position which in turn enhances innovative outcome. In other words, firms' capabilities play a moderating role between network position and innovation (Boari et al., 2017). I take a step forward and argue that absorptive capacity plays a mediating role between centrality and innovation. Thus, I contend that it is not the central position that enhances innovation; instead, it is the absorptive capacity of a firm that increases its innovative outcome. The direct relationship between the number of ties and innovation exists because central firms also have a high level of absorptive capacity. I argue that once I control for absorptive capacity, the direct effect of centrality will disappear. Therefore, in this paper I test the mediating role of a central position in the advice-giving and advice-seeking network. I submit the following hypotheses:

H5: Absorptive capacity mediates the direct effect of advice-seeking ties on innovation.

Figure 5-1 shows that the relationship between advice-giving and advice-seeking ties, and innovation. It also illustrates the mediating role of absorptive capacity between advice ties and innovation. The figure presents the conceptual framework of the current study. The figure shows that the degree centrality has a direct effect on the innovation outcome of firms. Moreover, my model proposes that absorptive capacity mediates the relationship between the advice-seeking and advice-giving ties and innovation. That is, the advice-seeking and advice-giving ties also have an indirect effect on innovation via the firm's absorptive capacity. The figure also suggests a direct relationship between relational embeddedness, which is strong ties and weak ties, on the innovation output of firms.

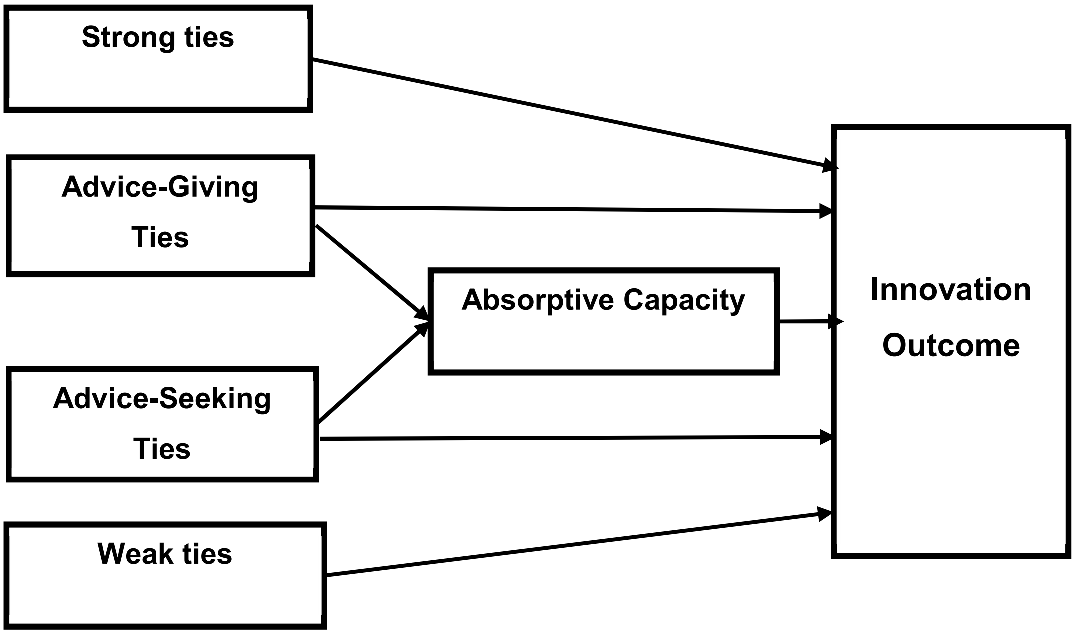


Figure 5-1 Impact of structural and relational embeddedness on innovation, and the mediating role of absorptive capacity

5.4 Data and methodology

5.4.1 The empirical context

The context of this empirical study is a textile industrial cluster in the city of Lahore, Pakistan. Many researchers highlight the importance of innovation in mature industrial clusters (Casanueva et al., 2013; Zaheer and Bell 2005). Lahore is the second most populous city in Pakistan with a total population of around 10.6 Million in 2016 (Demographia, 2018). The city is the hub of many industries including textile and clothing. The textile Industry is the backbone of the economy of Pakistan. It contributes to around 54% of the country's total exports, employs 40% of the industrial workforce and also accounts for 8% of the total GDP (Golra et al., 2011; Pakistan Textile Policy, 2014-19). The industry is scattered across the country in the form of several clusters. The most prominent textile industrial clusters are located in the cities of Lahore; Faisalabad; Sheikhupura; Sialkot in the province of Punjab; and Karachi, Sukkur and Hyderabad in the region of Sindh.

According to a census of manufacturing industries conducted by the Pakistan Bureau of Statistics (PBS) in 2005-06, the city of Lahore accounts for approximately 18% of the total textile and clothing manufacturing firms in the province of Punjab and about 10% in Pakistan (Pakistan Bureau of Statistics, 2013). The census results reported 131 textiles and 39 wearing apparel firms from Lahore. These firms are involved in almost all stages of the textile value chain, i.e. yarn manufacturing, knitted and woven fabric manufacturing, dyeing, printing and finishing of fabric, apparel and made-ups manufacturing. Further, they are clustered mainly in four different locations: Raiwind-Manga Road, Ferozepur Road, Bhaiperu-Multan Road, and Defence Road as shown in Figure 2-1. The Lahore textile cluster is the home to some of the most prominent textile firms and their subsidiaries that lead the textile industry in Pakistan.

In my sample, on an average basis, each firm employs around 1700 workers, with a standard deviation of approximately 1400. The maximum number of employees was reported to be 7000, and the minimum was 500. I collected data from large-scale firms because of the following reasons. First, large firms are registered with All Pakistan Textile Mills Association (APTMA), which is the most prominent statutory, regulatory body and represents all the critical textile players in the Pakistani textile industry. A registration with APTMA ensures that member firms organise themselves in their financial, operations and organisational matters. Second, there is a large number of unorganised firms operating in the cluster which do not maintain proper records of their business operations. Moreover, these firms do not register with any statutory or regulatory body, or any government department which raises ambiguity about the exact number of these firms operating in the cluster. Third, in order to apply the whole network approach as part of a social network analysis, I decided to use the roster recall method for data collection which eventually requires a complete list of firms.

5.4.2 Sample and instrument

I did not use any sampling technique, and the data was collected from all large active scale textile firms located in the four municipalities in the city of Lahore. The list of firms was obtained from the website of the All Pakistan Textile Mill Association (APTMA). According to the list, eighty-four large-scale textile firms were operating in the local cluster.

Following the APTMA statistics, I limit the sample size to seventy-three firms because some of the firms have closed their operations due to the crisis. The latest textile policy document of the Government of Pakistan also highlights that some firms have ceased operating in the last ten years due to the severe energy crisis (Pakistan Textile Policy 2014-2019, 2015). Before the final data collection, I conducted a pilot study. The pilot was done, firstly, to test the survey instrument dealing with firm characteristics, innovation practices and performance; and secondly, to finalise the number of active firms to include in the roster for the collection of inter-organisational relational data.

Four firms were visited during the pilot study that were located in the city of Lahore, Pakistan. Two firms were independent units, and both of them were fully equipped with a complete setup of the manufacturing process for their product (which means they do not outsource any of the production processes for their product). The other two firms are a part of a group of companies. One of these firms belongs to a group that has versatile products, including from textiles and garments, matrices, cutlery, motorcycles, tractors and so on. However, I visited their apparel manufacturing unit only, which is fully equipped with a complete range of equipment for the manufacturing process. The other firm was a part of a group that has multiple units of garment manufacturing and therefore deals with garment products only.

Data was collected through face to face semi-structured interviews. Seven interviews were conducted within four companies. The interviewees/respondents were the managers of the firms working in R&D, Product Development (PD) and Production management departments. Before asking the questions, the researcher explained the purpose of the project to the interviewees and then asked their consent for the use of data for research and dissemination

During the pilot study, managers of local firms also confirmed that a small number of firms have shut down their operations due to the energy crisis. After the pre-test, I revised my survey instrument and finalised the universe of manufacturers within the cluster. Since Creswell (2014) states that a respondent in a pilot study cannot be part of the actual study, I did not interview heads of departments in the pilot and instead interviewed the middle managers. I adopted this strategy so that I could approach the head of departments in the final study.

5.4.3 Data collection

In order to investigate the impact of structural network positions of firms on their innovation, I collected micro level attribute data and dyadic level relational data from seventy-three textile firms in the Lahore textile cluster. My unit of analysis in this study is the manufacturing firms in the textile cluster. The attribute data was collected through face to face interviews, using a pre-tested survey questionnaire from the key personnel responsible for the management of production operations and research and development. In this study, I decided to administer the survey through a face-to-face interview with the senior managers and directors of firms. I adopted this method for two reasons. First, to ensure respondents' accuracy and avoid misinterpretation of the questions. Second, the top managers are considered as a critical source of technical and business knowledge in the local industry. Huber (2013) also suggests that the most critical and unique knowledge sources are usually obtained by personal knowledge networks (social network) of senior-level managers.

To collect network-level or relational data, I asked respondents to choose from a roster of 73 firms from which respondents regularly asked for technical advice. This 'roster recall method' has been widely used by scholars to collect whole network data (Balland et al. 2016; Boschma and Ter Wal, 2007; Giuliani and Bell, 2005; Giuliani, 2007, 2013; Morisson and Rabellotti, 2009) as it reduces selectivity bias in the responses of personnel due to memory effects (Molina-Morales et al., 2015). Relational data allowed the creation of a directed squared matrix with $n=73$ actors, and it can be represented as binary $n*n$ graph $x = (x_{ij})$, where $x_{ij}=1$ when actor *'i'* discloses a technical advice link to actor *'j'*, and $x_{ij}=0$ otherwise. A social network analysis software package UCINET 6 was used to process and analyse the relational data (Borgatti, Everett, & Freeman, 2002). This data was used to create explanatory network variables (e.g. in-degree and out-degree centrality, density and structural holes). I asked the following two questions from the firms to gather relational data:

c) *When you need technical advice on product development/innovation, to which of the local firms mentioned in the roster (list) do you turn?*

d) *When you need technical advice on process improvement/innovation, to which of the local firms mentioned in the roster do you turn?*

These two questions yielded two different technical networks, namely the product advice network and the process advice network. The Pearson correlation between the two networks is 0.447, which means there is 44.7% overlap between the ties of the two networks. I merged these networks to produce a single technical advice network and calculated the network structural variables.

Additionally, I gathered secondary data from other sources, such as company websites, government websites and trade association websites. The overall information was used to create dependent and explanatory variables. Table 5-1 presents descriptive statistics on firm-level attributes and network level variables. Firm-level characteristics include size, age, R&D, managers' qualifications, absorptive capacity, trade association memberships, while network-level characteristics include in-degree centrality (advice-giving), out-degree centrality (advice-seeking), structural holes, strong ties, weak ties and density.

5.4.4 Measures

5.4.4.1 Dependent variable

I did not measure innovation by following the standard questionnaire used in innovation surveys and introduced a new measure. I measured innovation activity by counting the number of international compliance certifications obtained by firms for quality and environment management systems, such as ISO 9001:2015, OEKO-TEX, GOTS, ISO-14001:2015, etc. I understand that this measure generally represents quality management capability of firms; however, some of these accreditations are mandatory in order to process specialised materials. For instance, GOTS certification is compulsory to process organic cotton products and similarly OEKO-TEX certification is mandatory for processing flame-retardant finishes. Thus, I argue that this measure is particularly valid in my context because leading global brands and global buyers demand compliance from local firms in various dimensions, such as quality, safety, environment and social standards which is a challenge for local firms and is difficult for low capacity firms to achieve (SMEDA Pakistan 2018).

I have adopted this unique measure of innovation for several reasons. First, this different innovation measure was suggested by the respondents during the interviews[13]. They argue that international certifications are critical to new markets and customers because most international buyers have associated their new orders with global compliance standards. The firms who meet the compliance standards get the orders. In order to obtain these certifications, firms have to improve their production systems and this requires the introduction of new processes. Similarly, firms have to improve the quality of

[13] Respondents argue that textile is a traditional industry, and the development of new products and processes is a routine task, which makes it difficult to identify significantly improved innovations. Moreover, innovation frequency in one industry cannot be considered with another industry. For example, innovations in a garments manufacturing unit cannot be compared with a yarn manufacturing firm because of difference in process and operations complexity. Therefore, it is very difficult to differentiate between an innovation and a routine development, as well as to consider relative innovation count. Likewise, firms develop new processes and techniques to improve efficiency regularly, which again is difficult to differentiate routine improvement in process from significantly improved process.

products by complying with new product-quality standards. If firms do not comply with global standards of product and process management, it is highly likely that the leading global brands will not place their order for new products with these firms, which in turn may limit their innovative capacity. Innovation scholars have highlighted that the lack of interaction with external players can negatively affect local firms' learning and innovation. For instance, Boschma and Ter Wal (2007, p.181) aver that "when district firms become too much inward looking, their learning ability may be weakened to such an extent that they lose their innovative capacity and are unable to respond to new developments".

The second justification for my innovation measure is my research setting in this paper, which is a local textile cluster based in a developing country. Cirera and Muzi (2016) argue that most questionnaires used in innovation surveys are based on the Oslo manual, which was developed to measure innovation in advanced countries; therefore, it is not suitable to use the Oslo questionnaire in the context of developing countries because understanding the innovation concept in developing countries is different from developed countries. Authors raise the concern that respondents in developing countries who are asked whether they have introduced a significant new product or process may respond differently from one another because it becomes difficult to gauge how significant the innovation efforts are. Moreover, Casanueva et al. (2013) argue that obtaining objective assessments of innovation levels is difficult in traditional clusters, especially when dealing with a wide range of firms and productive systems, such as in textiles and the clothing value chain. Therefore, my measure of innovation provides a relatively proper measure. I counted the total number of certifications displayed by the firms on their websites[14].

[14] All firms in our sample have maintained their proper websites. In most cases the websites of firms have a separate section of compliance certificates. In other cases, compliance certificates were highlighted on the introduction/profile pages of firms.

5.4.4.2 Independent variables

The key independent variables in my study are the network structural and relational variables. To create network variables such as centrality, density and structural holes, I used UCINET VI software (Borgatti, Everett and Freeman, 2002). The theoretical formulas for the network variables are discussed as follows:

My first independent variable to measure structural embeddedness is *degree centrality*. It captures the number of ego's direct relationships to all other alters. In my study, the network is directed in nature. Therefore, I can calculate the in-degree as well as out-degree centrality. The in-degree centrality captures the idea of popularity, or the advice-giving role, which is when several other firms seek out advice from the ego. The out-degree centrality captures the idea of activity or the advice-seeking role, which is when the ego seeks out advice from many other alters. I calculated both degrees using the following formula:

Degree centrality, DC (ni) = d(ni)

Where d (ni) is the sum of the nodes adjacent to that node. I calculated both the in-degree (advice-giving) and out-degree (advice-seeking) centrality.

In addition to degree centrality, I calculated Bonacich's (1987) *power centrality.* I did it to check the robustness of my model. The power centrality captures the strength of the focal firm, and it is defined by the sum of the power of the ego's alters (Whittington et al., 2009). If the ego connects to other well-connected actors, then it has high Bonacich centrality. Similar to the degree centrality measure, I calculated two measures of Bonacich power centrality that is one for advice-seeking ties, and other for advice-giving ties.

My paper also theorises the effect of relational embeddedness on innovation. I identify strong and weak ties to examine the influence of relational embeddedness on firms' innovation. To measure strong ties, I consider only the overlapping links in my network, that is, the links that represent both the product and process advice. I argue that when a firm establishes multiple linkages with another, or it seeks multiple pieces of advice from the same firm, then it is considered a strong relationship. On the contrary, when a firm shares a single relationship with another firm, then I can consider it a weak tie.

To measure *strong ties and weak ties,* I created two additional networks. The first network consists of only the overlapping ties (strong-ties network) and the second network consists of all other ties minus overlapping ties (weak-ties network). I then counted the network size of each firm in the strong-ties network to measure *strong ties* associated with each firm. Similarly, I counted the network size of each firm in the weak-ties network to calculate the *weak ties* of each firm. The rationale behind this approach is that when two firms are connected via more than one type of relation, or they are sharing more than one type of resource, which in turn increases trust among partners. Thus, it can be assumed that their relationship is stronger than those who share only one type of relation.

In this study, *absorptive capacity* is one of the critical variables and is a measure of a firm's knowledge absorption capability. Previous studies have measured absorptive capacity by accessing the human resource, research and development efforts of firms. For instance, scholars measure absorptive capacity through several methods, such as a percentage of skilled employees (Molina-Morales et al., 2015), R&D spending (Cohen and Levinthal, 1989; Presutti et al., 2017), R&D intensity (Tsai, 2001), patent productivity in a specified time (Boschma et al, 2015) and applying principal component analysis (PCA) on various human resource and research parameters (Boschma and Ter Wal, 2007; Giuliani and Bell, 2005; Giuliani, 2007; Giuliani, 2013). This study follows the latter procedure and runs a principal component analysis (PCA) on three parameters that is human resource, R&D and internationalisation efforts of firms to extract a measure of absorptive capacity from three main components (please see appendix A for detail on PCA).

5.4.4.3 Control variables

I also control for several variables that can affect the innovation outcome of firms. First of all, I control the *size* of firms because large size firms have access to more resources than the smaller firms and hence are often more innovative. I measure size by taking the logarithm of the number of permanent employees. Size is a continuous variable. I also control for the *age* of firms. I measure the age of a firm by subtracting the birth date from the date I collected the data. I then calculate the square root of the age of the firm. Age is a continuous variable. Several studies have shown that older firms are often less innovative than the younger firms because of several reasons; for example, substantial investments in traditional processes which require massive investment for upgrading.

In addition to age, I also control for the *status* of the firm. I define high-status firms as those firms who hold memberships of several trade associations. High-status firms are more innovative than other firms because of their membership in different power groups that allows access to a wide range of resources as well as an opportunity to influence the government's industrial policy. Non-affiliated firms do not have access to such resources and power centres. There are fifteen trade associations in the local textile and related industries. I count the number of trade association memberships of each firm. I collected that information from the latest members' directory of each of the fifteen trade associations. Where I were unable to access the member's directory, I explored the firm's (or its parent company's) website to check their trade memberships because firms often display their association memberships on the websites to attract customers[15]. Status is a continuous variable.

I also control the *qualification of managers* to control for the education bias. Some respondents in my sample are non-degree holders who became managers because of their work experience, some are engineering degree holders, and the rest are business degree holders. The education skills of

[15] We did not have to use this strategy for many cases

managers can influence the innovation of firms (Fitjar and Rodríguez-Pose, 2015). This is especially crucial in my study because I are dealing with technical innovations and thus expect that managers with an engineering degree are likely to be more innovative than the other two groups. Finally, I control for *geographical location*. Firms in my sample are located in four different municipalities. Therefore, I decided to control any effect of geographical location on innovation. The next section presents my estimation model and results.

Finally I control for some structural variables. First, I control for *density*. It is an important control variable. It captures the idea of network closure (Coleman 1988). High density increases trust and reduces opportunistic behaviour among connected partners. Especially in a mature cluster, density plays a crucial role by sanctioning opportunistic behaviour. I measure density by an actual number of ties in the ego's network to the maximum possible ties. I use the following formula to calculate density:

Density = actual ties/total possible ties, D=2N/n (n-1)

Where *'N'* is the actual ties between alters (excluding ties to ego) to the total possible ties, that is, *'n (n-1)'*.

Among the network variables, I also included *structural holes* as a control variable (Burt, 1992). Structural holes provide access to diversified information which can be useful to create innovations. I calculated the constraint score using the UCINET VI software. A higher constraint score represents low access to bridging opportunities and indicates that an actor is constrained by its contacts, which decreases access to the structural hole. The formula I use for the constraint is:

Constraint = $P_{ij} + \sum P_{iq}P_{jq}, q \neq i, j$ (Burt, 1992: 54)

Where P_{ij} is the strength of direct ties, $\sum P_{iq}P_{jq}$ is the sum of the indirect tie strength from i to j via all q. To calculate the structural holes access, I subtracted the firm's constraint score by 1 for all non-zero values and zero for all other values.

5.5 Estimation model

To test my hypothesis, I analysed six models using ordinary least squares regression technique with IBM SPSS Statistics version 22. I used the following estimating equation:

Innovation = $\propto_0 + \beta_1(Advice - giving\ tie) + \beta_2(Advice - receiving\ tie) + \beta_3(Strong\ tie) + \beta_4(Weak\ tie) + \beta_6(Absorptive\ capacity) + \beta_7(Controls) + \varepsilon$ --- *Eq.1*

Where $\propto_0$ is the constant intercept, β_i is the regression coefficients for the main effect variable and ε is the error term. Table 5-1 represents the descriptive statistics and the correlation coefficients of the main effect variables and the control variables. Table 5-2 presents the regression estimates for all five models. The models are significant and the R-squared as well as Adjusted R-squared values show that my models are stable and also that the explanatory power of my models is good. I also conducted the collinearity diagnostic and checked the value of the variance inflation factor (VIF). The VIF values of all structural embeddedness and control variables are well below the standard critical threshold value of 10 (Mayer 1990, Cohen et al. 2003, Field 2009) and even below the more restricted value of 4 (O'brien, 2007), which suggests that multi-collinearity is not an issue in my models involving structural embeddedness. However, when I add relational embeddedness variables in the model, which are the strong and weak ties, the VIF values go above 10. These variables have a strong correlation with the advice ties. One of the potential reasons is the operationalisation of strong and weak ties. Since my advice network is composed of both the product and process innovation ties, I consider a tie as weak when firms exchange only one type of advice (e.g. either product or process), and when they share both types of advice, I consider it as a strong relation among partners. Therefore, to deal with the multi-collinearity problem, I rely on the partial models in testing my hypothesis related to relational embeddedness. This procedure has been commonly used in prior research (Iurkov and Beniti 2018; Kraft and Bausch 2018; Soltis et al., 2015).

5.6 Results

This section presents the results of the paper and discusses the impact of different structural and relational embeddedness variables on the innovation outcome of firms. The descriptive statistics are presented in Table 5-1 followed by statistical models in Table 5-2. In order to test the hypothesis, I ran six statistical models. In addition to the tables, figure 5-2 presents the results of the Sobel test for mediation. The first model in my study includes firm and geographic control variables. As expected, most of the control variables are statistically significant. My first control variable *age* is negative but not significant, which shows that age does not affect the innovative outcome of firms. In contrast, *size* is positive and highly significant which confirms previous research that size is an essential factor. The innovative outcome of a firm increases with the increase in its size. I also controlled for the *status* of the firms. Previous research considers status as a symbol of quality in clusters (Giuliani 2013). High-status firms are prominent firms and better than other firms regarding quality. If status represents quality, then high-status firms should be relatively more innovative than the low-status firms. My results confirm my expectations, and the coefficient of status is significant and positive.

I also controlled for the education and skills of the top manager as well as the geographic location of firms. I included engineering-graduate managers and managers with business qualifications in my model. I kept non-engineering graduates as a reference category. My finding is as per my expectation. First, a firm whose top manager is an engineering-graduate shows a positive and significant relationship with innovation output. The relationship between business graduate managers and innovation also shows a positive and significant relationship[16].

These findings suggest that for technical innovations, the top managers with technical/engineering qualifications perform better than non-degree holder managers, and also relatively better than a top manager with both a technical and business qualification. To gauge the effect of geographic location, I first divided the geographic areas into four different zones. Afterwards, I tested zone2, zone3 and zone4 against the reference category of zone1. Zone4 shows the most substantial positive and significant impact on innovation, whereas zone2 shows a negative and significant impact on innovation. Zone3 also shows a positive and weak impact on innovation. These findings suggest that some geographic areas may be better equipped with facilities. Therefore, firms situated in such areas perform better than others and vice versa.

In models 3, I included network level controls. I find that the coefficient for density is positive and significant ($\beta = 1.17$, $p<0.05$), which suggest that, in a mature industrial cluster, dense connections positively contribute to the innovation outcome of the focal firm. While dense connections contribute positively to the innovation outcome of a focal firm in a mature industrial cluster, structural holes can have a negative impact on innovation outcome. Due to homogeneity in information in the cluster, structural holes access can result in more costs than benefits. Therefore, I expect a negative impact of the structural hole on innovation outcome in a mature industrial cluster. Although I find a negative impact of structural holes accesses on innovation output, the coefficient is not significant.

[16] Our reference category is a firm whose top manager has no professional graduate level qualification.

Table 5-1. Correalation and descriptive statistics

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Absorptive capacity	1																		
2	Status	.550**	1																	
3	Age	-.142	.167	1																
4	Size	.374**	.108	.133	1															
5	Density	.398**	.163	-.069	.264*	1														
6	Structural Holes	.189	-.097	-.164	.218	-.058	1													
7	Advice-giving ties	.566**	.309**	.013	.250*	.590**	-.137	1												
8	Advice-seeking ties	.215	-.009	-.079	.286*	.603**	-.046	.475**	1											
9	Advice-seeking (Power)	.443**	.259*	.026	.202	.571**	-.138	.933**	.439**	1										
10	Advice-giving (Power)	-.149	-.130	-.044	.131	.486**	-.069	.352**	.722**	.417**	1									
11	Strong ties	.459**	.292*	.066	.193	.478**	-.028	.672**	.569**	.619**	.391**	1								
12	Weak ties	.350**	.081	-.072	.298*	.704**	-.181	.782**	.756**	.739**	.575**	.402**	1							
13	zone1	-.140	-.120	-.028	-.306**	.025	-.215	.135	-.074	.190	.102	.026	.066	1						
14	zone2	-.274*	.057	.156	-.117	-.158	.003	-.173	-.033	-.159	.072	-.018	-.138	-.426**	1					
15	zone3	.259*	-.031	-.089	.383**	.064	.237*	-.088	.092	-.179	-.187	.019	-.034	-.549**	-.254*	1				
16	zone4	.223	.203	.002	.119	.067	.007	.143	.047	.174	.033	-.061	.136	-.313**	-.144	-.186	1			
17	Non-engineer	-.109	-.212	-.032	.080	-.305**	-.037	-.311**	-.309**	-.272*	-.229	-.328**	-.257*	-.073	-.156	.206	.035	1		
18	BSc Engineer	-.025	.155	.036	-.185	.127	.119	.150	.036	.184	.021	.103	.024	.065	.037	-.198	.104	-.552**	1	
19	Engineer+MBA	.119	-.010	-.016	.153	.098	-.110	.077	.209	.004	.163	.146	.181	-.017	.083	.066	-.152	-.163	-.732**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 5-2. Regression of Innovation with structural and relational embeddedness

Model	1		2		3		4		5		6	
									Robustness Check			
		(S.E)		(S.E)		(S.E)		(S.E)		(S.E)		(S.E)
Intercept	-2.52	1.135	-2.62	1.08	-2.215	1.08	-1.107	0.83	-2.29	1.02	-0.99	0.918
Controls												
Age	-0.09	0.08	-0.13	0.08	-0.07	0.08	0.004	0.06	-0.07	0.07	0.001	0.07
Size	0.90*	0.38	1.01**	0.36	.75*	0.37	.69*	0.30	0.80*	0.35	.62*	0.3
Status	0.46*	0.17	0.55**	0.17	0.40*	0.18	0.04	0.15	0.31+	0.17	0.07	0.16
Zone 2	-0.57	0.29	-0.64*	0.28	-.47+	0.28	-0.37+	0.22	-0.44	0.26	-0.37	0.22
Zone 3	0.66*	0.28	0.56*	0.26	.73**	0.26	0.35	0.22	.49+	0.26	0.31	0.23
Zone 4	1.24***	0.37	1.40***	0.35	1.23**	0.34	.78**	0.28	1.14**	0.35	.79**	0.29
BSc-engineer	1.20***	0.35	1.13**	0.34	1.14**	0.35	1.18***	0.28	1.07**	0.32	1.05***	0.28
MBA degree	1.02*	0.28	1.02*	0.26	1.16**	0.26	0.92**	0.21	1.15**	0.25	0.83*	0.22
Network Controls												
Density					1.17*	0.51	0.47	0.43	1.22*	0.49	0.68	0.43
Structural Holes					-0.12	0.63	0.004	0.51	0.28	0.60	-0.25	0.52
Main effects												
Relational embeddedness												
Strong ties			0.16**	0.06								
Weak ties			-0.9**	0.03								
Structural embeddedness												
Advice-giving ties (indegree)					0.09*	0.04	-0.009	0.03				
Advice-seeking ties (outdegree)					-0.12**	0.04	-.08*	0.04				
Advice-giving ties (indegree bonacich)									.06**	0.02	0.014	0.021
Advice-seeking ties (outdegree bonacich)									-.08***	0.02	-0.03	0.02
Mediator												
Absorptive capacity							.71***	0.12			.61***	0.13
R-squared	0.52		0.6		0.63		0.77		0.67		0.76	
Adjusted R2	**0.46**		**0.54**		**0.56**		**0.72**		**0.6**		**0.7**	
Change in R2	0.52		0.08		0.1		0.13		0.14		0.09	
F for change in R2	8.79***		5.94**		4.39**		35.13***		6.46***		22.08***	
Max VIF	1.43		1.56		2.2		2.6		2.17		2.8	

*Significance codes: P<0.001*** ; P< 0.01**; P< 0.05* ; P<0.1* $^{+}$

In model 2, I tested the impact of relational embeddedness on innovation as theorised in hypotheses 1 & 2, which is to test the impact of strong and weak ties on innovation. I hypothesised that strong ties would positively influence the innovation of firms in the mature industrial cluster. The coefficient is positive ($\beta = 0.16$) and strongly significant ($p<0.01$), therefore I can corroborate hypothesis 1. Contrarily, the coefficient for weak ties is negative and also strongly significant ($\beta = -0.9$, $p<0.01$), which shows that weak ties in a mature industrial cluster decrease innovation output. Therefore, I can also confirm hypothesis 2.

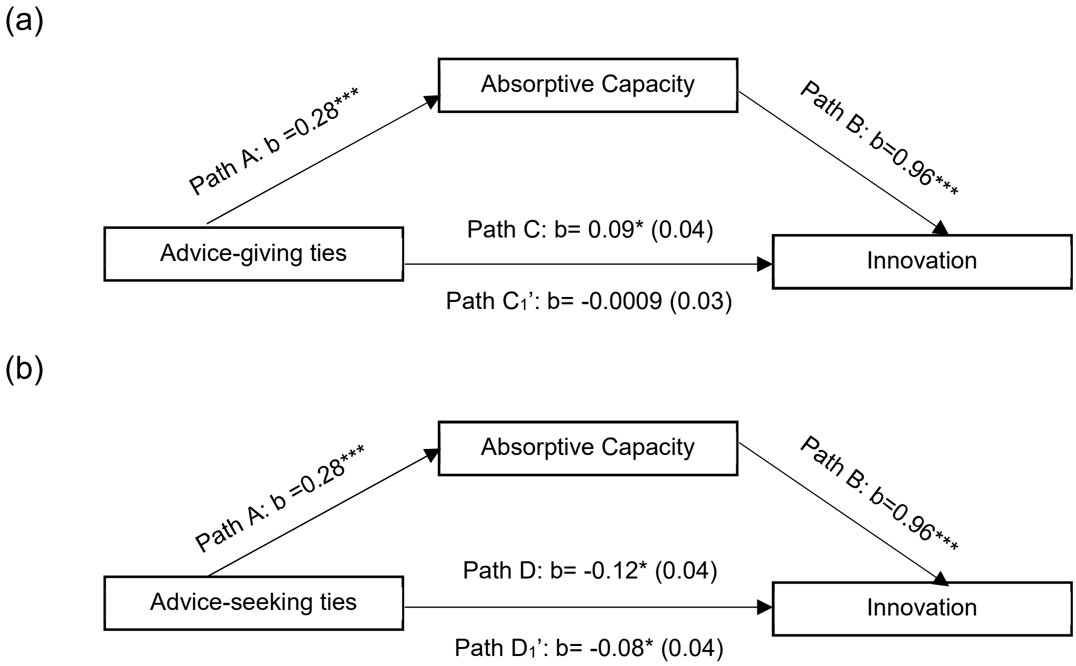
In models 3, I tested hypothesis *H3* and *H4*. I investigate the impact of central position on innovation in advice-giving and advice-seeking ties. For *H3*, I find that the coefficient for advice-giving ties is positive and significant ($\beta = 0.09$, $p<0.05$). Similarly, I also find support for hypothesis *H4*. The coefficient is negative and significant ($\beta = -0.12$, $p<0.01$). These results support my idea that in a mature industrial cluster, where the information available is likely to be redundant, and the innovation output of those firms who seek advice from many other firms can be harmed.

In model 4, I test hypothesis *H5* that absorptive capacity mediates the relationship between advice-giving and advice-seeking ties, and innovation. My results show that as I enter the variable of absorptive capacity in model model 4, the coefficient of advice-giving ties becomes insignificant, while the coefficient of advice-seeking ties is partially reduced. Therefore, I can confirm that absorptive capacity completely mediates the relationship of advice giving centrality and partially mediates the relationship of advice seeking ties on the innovation outcome.

In Model 5 and 6, I check the robustness of my model 3 and 4. I used Bonacich's power centrality to further confirm my hypothesis of centrality in advice-giving and advice-seeking ties. Here, I expect that when a firm seeks advice from several other firms who are well connected in their network in a mature industrial cluster, then this advice-seeking behaviour may have negative consequences on the firm's innovation outcome. I find a negative and highly significant coefficient (β = -0.08, p<0.001). By contrast, I find that advice-giving ties positively impact a firm's innovation outcome. The coefficient is positive and significant (β = 0.06, p<0.01).

I also used the Sobel test (Sobel, 1982) to validate the mediating effect. I tested for the mediating effect of absorptive capacity on the relationship between advice-giving and advice seeking ties, and innovation was tested using the indirect effect approach (Preacher and Hayes, 2004). Figures 5-2a, 5-2b, 5-3c and 5-3d present the results of the the Sobel test. I found that absorptive capacity was positively related to innovation as shown in figures 5a, 5b, 5c, 3d; Path B: b=0.96, p< 0.001). The Sobel test statistics also confirm the mediating effect of absorptive capacity for degree centrality in advice-giving ties (Z=3.64, p <0.001) and advice-seeking ties (Z=2.93, p<0.003), as well as for Bonacich centrality in advice-giving ties (Z=2.71, p<0.006) and advice-seeking ties (Z=3.52, p<0.001). My analyses demonstrated that when absorptive capacity is accounted for as a mediator, advice-giving and seeking ties no longer had a significant effect on innovation (see figure 5-2a Path C_1' & figure 5-3c Path C_2'). This finding suggest a full mediation effect in support of Hypothesis 7b for both degree centrality and Bonacich centrality measures. However, I find a partial mediation effect of absorptive capacity on advice-seeking ties when degree centrality is used (Figure 5-2b Path D_1'), while full mediating effect of absorptive capacity on advice seeking when Bonacich centrality measure is used (figure 5-3d Path D_2').

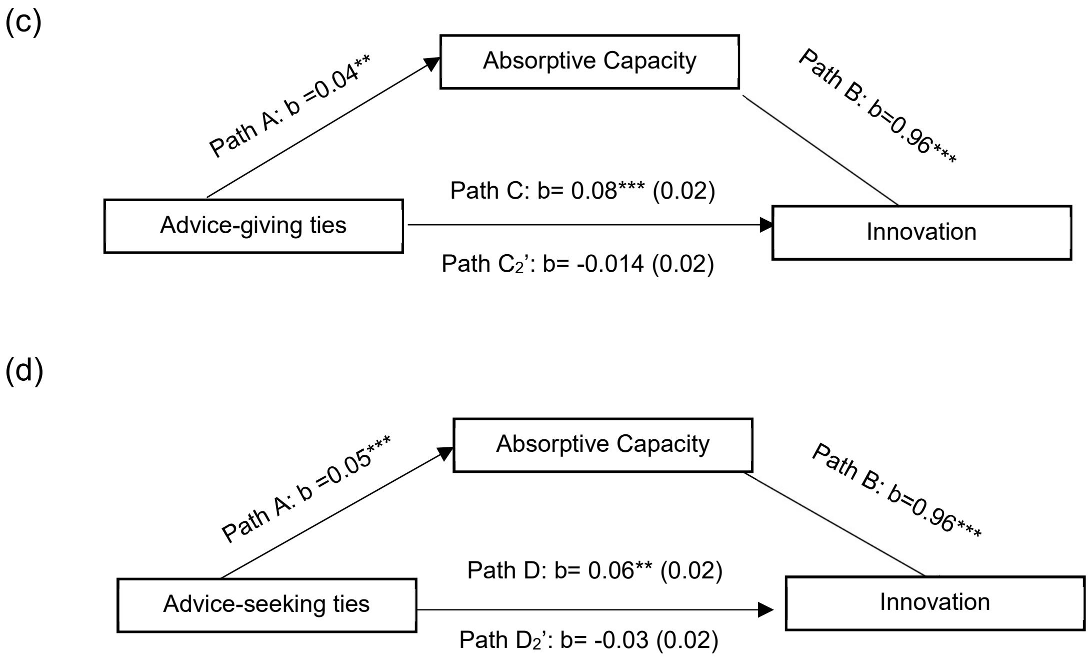
The results confirm that absorptive capacity significantly mediates the relationship between advice-giving and advice-seeking ties and innovation. Absorptive capacity is a partial mediator of advice-seeking ties for degree centrality. These findings highlight the essential role of absorptive capacity, which is crucial to gain access to the external sources of knowledge, especially in the context of a mature industrial cluster where information within the cluster is highly redundant, and new information is available from outside the cluster boundaries. Therefore, centrality is of secondary importance and absorptive capacity is a necessary capability.



Unstandardized coefficients reported above with standard errors in parentheses
Significance codes: $p<.1^{+}$, $p<0.05$ *, $p<.01$**, $p<0.001$*** (two-tailed).

Figure 5-2 Mediating Results (Degree centrality), (a) Advice-giving ties (b) Advice-seeking ties

<u>Sobel test for the robustness check model</u>



Unstandardized coefficients reported above with standard errors in parentheses
Significance codes: $p<.1^{+}$, $p<0.05$ *, $p<.01$**, $p<0.001$*** (two-tailed).

Figure 5-3 Mediating Results (Bonacich centrality), (c) Advice-giving ties (d) Advice-seeking ties

5.7 Discussion and conclusion

Overall, my study finds support for most of my hypotheses and demonstrates that both the structural and relational embeddedness play a significant role in explaining the innovation outcome of firms. Notably, my empirical results widely support my rational to theorise the direction of a tie in examining the innovation output of firms. The findings regarding the structural embeddedness, on the one hand, suggest that the centrality in advice giving ties (popularity) has a positive and significant impact on the innovation output of firm in a mature industrial cluster. My findings are consistent with previous research (Casanueva et al., 2013; Gargiulo et al., 2009; Tsai, 2001) that found a positive impact of in-degree centrality on innovation outcome.

On the other hand, I find that centrality in advice seeking role (activity) has a negative and significant effect on the innovation outcome of firms. This finding is in contrast with Gargiulo et al. (2009) who found a positive sign of outdegree centrality. However, my results are in line with Hansen (2002) who found a negative relationship between advice seeking ties (outdegree centrality) and project completion time. I argue that these findings may be explained by considering the context of the study. Since the context of my study is a mature industrial cluster where heterogeneity among firms is low (Menzel and Fornahl, 2009), therefore, firms seeking advice from many partners are likely to receive redundant information, which can negatively affect their innovation outcomes owing to high cost of knowledge search. In this respect, my findings are also in line with Tan and colleagues' (2015) study, who found a negative relationship between centrality and innovation performance in a network of well-connected and active actors. However, these authors found a positive impact of centrality on innovation performance in a low-density network.

In addition to centrality, I also tested for the impact of structural holes and network density on innovation. The effect of structural holes is negative but not significant, whereas the effect of density is positive and significant. My findings on structural holes are in line with Zhang et al. (2019) who show that the impact of structural holes on innovation is not significant in the Chinese context (a collectivist culture), but significant in the western context. The negative sign of structural holes in my findings is consistent with previous studies (e.g. Tan et al., 2015; Xiao and Tsui, 2007) which found a negative and significant influence of structural holes on the outcome. This finding is in contrast with several studies in the western context (e.g. Burt, 2004; Zaheer and Bell, 2005) which found a positive impact of structural holes on performance.

My findings are consistent with other recent studies in the Chinese context which argue that structural holes can either have a detrimental effect or no effect on the performance of individuals and firms (Xiao and Tsui, 2007). Since Pakistani culture is also collectivist (Merkin, 2016), this can be one of the potential reasons I find a negative but insignificant influence of structural holes. Hence, my findings do not support Burt's (1992) argument that structural holes positively impact firms' innovation outcome.

My results on the positive impact of density are also consistent with previous research (Gilsing et al., 2008; Rowley et al., 2000; Tan et al., 2015), which found a positive and significant impact of network density and innovation outcome. These findings support Coleman's (1988, 1990) network closure argument that dense networks are beneficial for innovation outcome owing to high trust and cooperation among well connected actors. However, Gargiulo et al., (2009) argue that the benefits of network closure are contingent upon the direction of information flow. The authors showed that being an acquirer of information in a dense network positively influences bankers' performance, while density decreases the performance of a banker when they act as an information provider. I argue that there is a massive gap in this area and other researchers should extend my work to address similar research questions.

Another important finding of my study is the impact of relational embeddedness on innovation. I investigate the relationship between the strength and quality of ties on innovation outcome. My findings suggest that strong ties positively influence innovation outcome and weak links negatively affect the innovation outcome of firms in a mature industrial cluster. My results partially confirm the findings of Rowley et al. (2000) who found a positive impact of strong ties in the steel industry (exploitation context); however, they also found a negative effect of strong ties in the semiconductor industry. In a different study, Ruef (2002) found a negative influence of strong ties on innovation. The justification that Rowley et al. (2000) provided in support of their results is in line with my argument that the industry context plays a crucial role in determining the impact of critical factors. Since the context of my study is a mature cluster which comprises well-established norms and traditions, these strong social norms promote trust among actors and sanction opportunistic behaviour. Therefore, strong ties may facilitate complex and tacit knowledge transfer, which positively affects innovation. Hansen (2002) also found a positive and significant association between the strength of relations and project completion time. The negative and significant impact of weak ties on innovation performance is in contrast with previous studies (e.g. Batjargal 2003; Rowley et al., 2000; Ruef, 2002). These studies found a positive impact of weak ties on innovation. Possible reasons might be that trust is more crucial in mature industrial clusters and weak ties may lack high trust, which negatively affects innovation.

Finally, the most interesting finding of this paper is the mediating role of absorptive capacity. I hypothesise that the absorptive capacity mediates the relationship between advice-giving ties and innovation. I find a positive and significant relationship between advice-giving ties and innovation. However, absorptive capacity mediates this relationship. The potential reason might be that in a mature industrial cluster, where information is highly redundant inside the cluster boundaries, firms need to establish connections with partners outside the cluster to absorb and transfer external knowledge. Therefore, centrality in the network is not the actual reason that influences innovation because it does not provide direct access to external knowledge. Indeed, it is the absorptive capacity that allows access to new external knowledge which is crucial for innovation. My findings are consistent with other studies which have investigated the moderating role of absorptive capacity (Boari et al., 2017; Zaheer and Bell, 2005). These studies suggest that the impact of structural position is contingent upon the absorption capabilities of firms.

Chapter 6 Conclusion to the thesis

This concluding chapter accomplishes five key tasks. First, it summarises the key findings of the three research studies. Second, it highlights the overall contributions of the thesis. Third, it offers practical, policy and academic implications of the thesis. Fourth, it outlines the limitations of this study, and fifth, it presents future research directions.

6.1 Key findings of the thesis

The overall aim of this thesis was to improve our understanding of the antecedents and outcomes of multiple networks with a focus on innovation networks.

In undertaking three interlinked empirical studies, this thesis provides valuable insight from different theoretical perspectives that advances our understanding of the phenomenon of network formation among actors and the impact of structural embeddedness of these actors on their innovation performance. This thesis analysed the formation of product and process innovation networks. Each of the three studies addressed specific research question related to the innovation-oriented networking activities of actors. Data for all the three studies were collected from a textile cluster in Lahore, Pakistan through interview-based survey method. In total, 73 firms have participated in this study.

The first empirical paper examined the formation of product and process innovation networks by employing proximity framework to understand whether and how different dimensions of proximity influence the formation of product and process innovation networks. The impact of social, organisational, cognitive and geographical proximity dimensions on product and process innovation networks were analysed.

In this paper, I tested several hypotheses on the role of proximity dimensions in explaining the formation of product and process innovation networks. The key theoretical argument is that owing to the difference in the knowledge characteristics of product and process innovations; proximity dimensions may have a distinct impact on the network formation of the two innovation networks.

I used multiple regression quadratic assignment procedure (MRQAP) to test the relationship between proximity dimensions and innovation networks. I found support for most of my theoretical predictions. The key findings are that the impact of various proximity dimensions differs across product and process innovation networks. In particular, the role of non-spatial proximities (i.e. cognitive, organisational and social) play a relatively more important role in the formation of process innovations network than product innovations network. On the contrary, I found that geographical proximity is relatively more crucial for product innovations network than process innovations network. These findings suggest that the characteristics of tie play a crucial role in defining the impact of proximity dimensions. In terms of knowledge ties, this study suggests that the more the knowledge is tacit and systemic, the higher the likelihood that actors tend to collaborate with proximate partners and vice versa.

In line with the first study, the second empirical paper in this thesis also addressed the question related to the formation of networks. This paper focused primarily on the individual-level and network-level drivers of product and process innovation networks. This study examined whether and how individual characteristics of actors and network endogenous mechanisms influence the formation of product and process innovation networks. More specifically, the paper examined the phenomenon of social selection and network self-organisation in the formation of product and process innovation networks. The phenomenon of self-selection focuses on the role of individual-level characteristics of actors in shaping network formation, while network-self organisation focuses on the structural properties of networks in shaping further collaborations.

In this paper, I tested six hypotheses. This paper employed exponential random graph models (ERGM). I used ERGM because it allows incorporating the node-level, dyadic-level and structural-level variables simultaneously to test a variety of research hypothesis (Broekel and Hartog, 2013). I showed that the role of absorptive capacity is important for both product and process innovation networks; however, I found that the impact was higher for product innovations network. Second, I demonstrated that innovative firms are less likely to collaborate with other firms in both product and process innovation networks. This is an interesting finding as it suggests that owing to high competition in the market, innovative firms do not see the benefit in interacting with other local firms for seeking product and process-related advice. The paper also analysed the role of business relations among firms. I found that business relations were positively related to both the product and process innovations advice sharing. This finding suggests that business relations help firms gather ideas on new products and technologies. Furthermore, I examined whether endogenous network mechanisms play a distinctive role in the formation of product and process innovation networks. My findings suggest that the role of structural characteristics differ across the two innovation networks. The coefficients of activity and popularity were positive and significant only for process innovation network and did not have a significant impact on product innovation network. Similarly, transitivity was found to be significant for both networks; however, the coefficient was higher for the process network.

Finally, the third paper took a step further and instead of examining the formation of networks, this paper addressed the research question related to the consequence of network embeddedness. This study examined the influence of firms' structural and relational embeddedness on their innovation outcome as well as it tested the mediating role of absorptive capacity between firms' prominent network position and innovation.

Using standard ordinary least square (OLS) regression model, I tested five research hypotheses in this paper. I found that a central position in advice-giving (popularity) and advice-seeking (activity) have a distinct impact on firms' innovation outcome. While centrality in advice-seeking ties negatively impact firms' innovative performance, the central place in advice-giving (popularity) positively impact the innovative outcome of firms. Moreover, I examined the impact of relational embeddedness on innovation outcome. The findings suggest that strong ties are more important than weak ties. Finally, the study also investigated the mediating effect of absorptive capacity and found a partial mediation role of absorptive capacity between advice seeking (degree) centrality and innovation. This finding suggests that having a central position is not enough to be innovative; it is indeed an indirect effect of absorptive capacity that results in higher innovativeness.

Amassing the findings of the three studies, this thesis provides a comprehensive account of the antecedents of product and process innovation networks. Considering different theoretical perfectives, the findings of this research provide an explanation that characteristics of ties play a significant role in defining the impact of different determinants of innovation networks. More specifically, it is shown that since product and process innovation ties differ in their knowledge characteristics, the impact of different factors such as proximity dimensions, absorptive capacity and other endogenous network variables on the formation of the two innovation networks also differ. Additionally, this thesis provides an insight into the role of structural and relational embeddedness of actors on the innovation outcome of actors by incorporating the direction of ties, which has been overlooked in previous studies.

6.2 Contribution of the thesis

The three studies that constitute this thesis provide several theoretical and methodological contributions. Using different theoretical perspectives, the first two studies contributes to the literature on multiple networks. The two studies provide a rich understanding of the determinants of product and process innovation networks. The third paper contributes to the studies on structural and relational embeddedness. It adds to the debate on the embeddedness of actors in asymmetric relation and the impact on innovation performance. Together the three studies contribute to the literature on innovation networks.

6.2.1 Theoretical contributions

The first paper contributes to the literature on proximity dynamics, multiplex networks and the geography of innovation. It particularly contributes to the recent debate on the impact of multiple proximity dimensions and multiple networks (Balland et al., 2016; Leszczyńska and Khachlouf; Quatraro and Usai, 2017), which argue that different types of knowledge and innovation may have a unique relationship with different proximity dimensions. The fundamental theoretical contribution of the first paper is that it analyses the relationship between multiple proximity dimensions and multiple innovation networks. More specifically, it theorises that the impact of proximity dimensions on process and process innovation networks differ from each other in a way that non-spatial proximity dimensions show a higher impact on process network than the product innovation network. The main argument is that characteristics of knowledge associated with the two innovations differ from each other, which in turn influence the impact of proximity dimensions. Similar concerns have been highlighted in recent network studies, which suggest that different types of knowledge require different types of proximities (Davids and Frenken, 2018; Quatraro and Usai, 2017).

The second paper contributes to the recent debate on underlying forces behind network formation and dynamics (e.g. Balland et al., 2016; Brailly, 2016; Brennecke and Rank, 2017; Lee and Lee, 2015; Molina-morales et al., 2015; Robins et al., 2012), which emphasises on the phenomenon of social selection and network self-organisation. These two concepts are associated with the social network perspective. These studies suggest that actors collaborate with other actors because of the similarity in their characteristics at the individual level. Moreover, they suggest that the endogenous network mechanisms (e.g. degree centrality, reciprocity and transitivity) play a crucial role in the formation and evolution of networks. This second paper of the thesis adds to this stream of literature and claims that product and process innovation networks differ from each other in their self-selection and network self-organisation mechanisms. Employing concepts from organisational learning (absorptive capacity), knowledge management (innovative capacity) and innovation networks (network structural properties) literature, this paper contributes to our understanding of these characteristics at individual-level, dyadic-level and structural-level distinctively influence the formation of multiple networks.

Findings of this study suggest that the characteristics of ties play a crucial role in explaining the phenomenon of self-selection and network self-organisation.

The third paper contributes to the debate on the asymmetry of network relations. This literature argues that network relations are seldom symmetric, and therefore, actors are often embedded in asymmetric relations (Hansen and Mattes, 2018). This asymmetry in relationships creates an imbalance in the flow of knowledge and resources which in turn influence the performance of individuals and firms, depending on their positions in the advice-seeking and giving network (Gargiulo et al., 2009; Soltis et al., 2013; Tan et al., 2015). In this study, I find that a central position in advice-giving (popularity) and advice-seeking (activity) have a distinct impact on firms' innovation outcome. While centrality in advice-seeking ties negatively impact firms' innovative performance, the central place in advice-giving (popularity) positively impact the innovative outcome of firms. Moreover, this paper contributed to the studies on relational embeddedness and innovation performance (Moran, 2005; Batjargal, 2007). This literature argues that embeddedness in strong and weak relations influence the performance of actors. Findings of my study add to this debate and suggest that strong ties are more important than weak ties for innovation performance in traditional industries such as textiles.

Together, the three studies contribute to three theoretical perspectives. First, it claims a contribution to proximity theory. More specifically, it contributes to the emergent literature on proximity and network dynamics (Balland et al., 2016; Davids and Frenken, 2018; Huber, 2012a; Torre and Wallet, 2014), network multiplexity (Bliemel et al., 2014; Lee and Lee, 2015; Leenders and Dolfsma, 2016; Leszczyńska & Khachlouf, 2018; Mazzola et al., 2016; Ram & Lori, 2014; Shipilov, 2012; Shipilov et al., 2014) and the geography of innovation activities (Balland and Rigby, 2017; Grabher et al. 2018; Grillitsch and Rekers, 2016; Shearmur and Doloreux, 2015; Shearmur et al., 2016). The thesis integrates the literature on multidimensional proximity and multiple networks to examine how different types of proximity (geographic, social, organisational and cognitive) shape the formation of product and process innovation networks. Second, the thesis contributes to the social network perspective. In particular, it contributes to the debate on social selection and network self-organisation in the second paper, which argues that firms and individuals select partners by similarity in individual attributes and that network ties tend to pattern themselves in certain ways (Rank et al., 2010; Robins, 2009; Robins et al., 2012). Third, the thesis contributes to the network and embeddedness literature by explicitly incorporating the direction of a tie in the analysis in the third paper. In this study, I show that the structural embeddedness in advice-seeking and advice-giving has different consequences on the innovation outcome. Finally, I contribute to the learning and innovation literature and demonstrate that the direct effect of structural embeddedness on innovation is mediated by absorptive capacity, which implies that merely network centrality is not enough for innovation instead higher knowledge absorption capability is essential to develop innovations.

6.2.2 Methodological and empirical contributions

This thesis is the first of its kind, which has applied both the standard statistical model and different types of advance social network models in a single study. The previous literature has not attempted to incorporate these models together owing to limitations of the data. Hence, the key methodological contribution of this thesis is that it employs both the multiple regression quadratic assignment procedure (MRQAP) and exponential random graph models (ERGM) in a single study along with an ordinary least square (OLS) regression model. Notably, in the innovation studies literature, scholars have either applied MRQAP or ERGM models to investigate the phenomenon of network formation. As far as I know, there is no single study in the innovation literature that has used the combination of both MRQAP, ERGM and OLS regression. Using these models together allow us to examine the determinants and consequences of networks in a single study, and therefore provides a comprehensive account of the phenomenon of networks and their importance in innovation. This thesis offers methodological advancements with regard to explicating how the node-level, dyadic-level and structural-level variables can be modelled in a single framework, not just to investigate the formation of the network but also to examine the impact of structural embeddedness on innovation performance.

In addition to the methodological contributions, this thesis has made a significant empirical contribution by investigating the product and process innovation network. These two networks provide interesting empirical evidence in to the literature on innovation networks. So far, most network studies have focused on single relationships to investigate the determinants of networks. While empirical evidence on multiple networks studies is growing, most innovation studies have focused on the distinction among business, market, knowledge and technical networks. This study is the first of its kind, which has proposed a clear distinction between product and process innovation networks. Although scholars have called for studies that can offer network studies by empirically distinguishing between incremental and radical innovations, this thesis responds to these calls and provide empirical a distinction between product and process innovation networks.

6.3 Implications of the thesis

The three studies in this thesis also have implications for policy, practice and education, which are discussed below.

6.3.1 Implications for practice

The first paper has important implications for production and R&D managers, and cluster policymakers. For R&D managers, my research suggests that managers should adopt different collaboration strategies for the development of product and process innovations. Since non-spatial proximities play a more crucial role in the formation of process innovations networks, managers may look for cognitively, organisationally and socially close partners when their focus is on introducing process innovations. My research further suggests that cognitive, organisational and social proximity is essential for product innovations, but they are less important as compared to process innovations. Reichstein and Salter (2006) argue that firms may focus on product or process innovation depending upon the competition in the market. In this regard, the managers adopt different strategies to compete in the market and make different strategic choices about different types of innovations. Therefore, the match between the type of innovation and proximity to an external source of knowledge or collaborating partner may be essential for implementing successful innovation strategies (Antonelli and Fassio, 2016). In this respect, managers who are focusing on developing new processes or products may need to consider their proximity to the external source of knowledge before making any strategic move. For instance, on the one hand, if the firms' proximity to the source is low and the knowledge to be acquired is complex, then they should firstly make an effort to reduce the level of proximity or to search for partners that are not too distant in proximity dimensions in order to ease collaboration and the subsequent transfer of required knowledge. On the other hand, if the knowledge required is simple, and it can be easily acquired from the external source, then firms' managers may not need to worry too much about the proximity issue. Finally, in a traditional industrial cluster where innovations are incremental, my research suggests that managers may tend to collaborate with relatively more geographically proximate partners for product innovations than process innovations.

The second paper also has important implications for R&D managers and production managers of clustered firms. My research suggests that R&D managers should organise their collaboration activities on the basis of the strategic focus of their firms. For instance, if the focus is on introducing process innovations, firms should position themselves in more dense networks with high clustering (transitivity) since this is beneficial to the transfer of tacit and systemic knowledge. Moreover, firms should position themselves in more central places because popularity and activity both tend to facilitate process-related collaborations which in turn can influence the transfer of knowledge. On the contrary, a central position in the network does not seem to be beneficial for product innovation-related interactions; thus the R&D managers should avoid positioning their firms in a central place when the focus is on developing new products. Insofar as transitivity is concerned, a less low clustering among firms may be better for product innovation. Nevertheless, reciprocal ties may be more useful for the product innovation than the process innovation networks, suggesting that firms focusing on product innovations should promote mutual exchange with their partners. Yet, mutual cooperation is less common, but still an important phenomenon in the development of process innovations.

Regarding the role of absorptive capacity, this paper suggests that managers working in firms having a higher level of absorptive capacity may expect to receive higher advice requests from other firms in the cluster. In turn, answering so many requests could distract the managers from fulfilling their own responsibilities and thus may affect their own performance. In this respect, managers should adopt a balanced approach. With respect to the role of innovative capacity, the results suggest that innovator firms are less likely to connect to other firms for both the product and process innovations, and therefore managers have to find other ways to get the required knowledge from other innovative firms.

The third paper also has implications for industry managers. The managers have to be careful while establishing ties with external firms. The critical point is that centrality in the network is not always beneficial, and particularly in informal relations, which are often asymmetric; thus, firms have to locate themselves in advice-giving and advice-receiving roles sensibly. My study suggests that a central position in the advice-giving is beneficial and the same position in the advice-seeking is detrimental for innovation. Moreover, strong ties promote trust so firms can focus on maintaining strong ties with other partners and should avoid weak ties with the other firms. A final and most important implication is that managers should focus on building a higher level of absorptive capacity of their firms because absorptive capacity is the fundamental source of external ideas and hence it helps firms to recognise and utilise the external knowledge. Managers should first build strong knowledge absorption capabilities and then establish linkages with the other cluster firms.

6.3.2 Policy Implications

In addition to implications for R&D managers, this thesis has implications for cluster development policymakers. For policymakers, the first two papers in this thesis suggest that if the aim of the policy is to achieve higher efficiencies in a region or industrial cluster through exploitation-focused innovations, policymakers should formulate policies that can promote an environment in which firms having similar attributes (e.g. firms belonging to same technological class and industry classification or firms that belong to the same parent company) find it beneficial to collaborate with each other. On the contrary, if the need is to promote diversification in a cluster through enhancing exploratory-focused innovations, then policymakers should formulate policies that can promote collaborations among heterogeneous (less proximate) partners so that diverse knowledge can be created.

Moreover, the focus of cluster policy should be on creating an environment in which innovative cluster firms find it beneficial to interact with the other local firms. In this way, less innovative firms may be able to learn from the leading innovative firms to improve the overall competitiveness of the cluster. Consequently, these interactions can have a fruitful impact on the socio-economic indicators at the national level.

6.3.3 Academic Implications

This research also has academic implications for both scholars and students of social sciences in general, and business and management studies in particular.

The literature on networks has grown tremendously over the last two decades. Numerous scholars from different scientific fields have contributed to the debate on how networks emerge and what are the consequences of structural embeddedness in these networks on different types of outcomes. Most of these network studies have focused on unitary networks and overlooked the importance of relational and structural embeddedness of actors in multiple networks. Studying multiple networks is important because research suggests that actors are simultaneously embedded in more than one relation (Shipilov et al., 2014), hence drawing conclusions based on single network studies may be biased. Therefore, scholars have called for more studies on multiple networks (Balland et al., 2016).

The first two studies in this thesis focus on the antecedents of multiple innovation networks. The findings of the first paper illustrate how different proximity dimensions influence the formation of product and process innovation networks in a distinct manner. Also, the findings of the second paper highlight the distinct impact of several explanatory variables on product and process innovation networks. These findings are particularly interesting for scholars undertaking research and teaching activities related to multiple innovation networks since empirical evidence in this area remains scarce. The results from these two studies can help in justifying why it is crucial to examine networks as multiple rather than unitary. In this way, the empirical results of these two papers can be used as examples in the courses on networks to explain the distinct impact of determinants of multiple networks.

6.4 Limitations and avenues for future research

This research is not without limitations; this the outcome of this study should be undertaken in light of its limitations.

First, the main limitation of the first empirical paper is that the data is collected from a single cluster which may be embedded in a specific local context, i.e. a specific industrial cluster located in a specific geographical locality. There can be several factors, which may differ across regions. For instance, local culture in different regions may differ from one another, which can influence the results. Pakistani culture is collectivistic, and hence, the results of this study may not be comparable to the results of a study conducted in an individualistic culture. However, scholars studying geographical clusters in countries with dominant collectivistic culture may replicate this study to test whether these results can be generalised. An interesting area would be to collect data from a variety of industrial clusters to understand the underlying forces of network formation.

Second, firms studied in this research were low to medium technology textile manufacturing companies; therefore replication of this study into a high technology sector may especially be very interesting because technological complexity of product and process innovations may be quite different in the high tech industry than a low and medium-tech industry. It might also be interesting to observe whether individual-level, dyadic-level and structural-level drivers of product and process innovation networks differ in a similar way in different industries.

Third, this study has analysed cross-sectional data and therefore unable to investigate the evolution and dynamics of networks, and their antecedents at firm-level, dyadic-level and structural level. For instance, Balland et al. (2016) and Giuliani (2013) used different methods to collect longitudinal data to investigate network dynamics. Future studies should collect longitudinal data so that the evolution and dynamics of the network can be better explained by examining network formation over time. Moreover, by collecting longitudinal data, other advanced network models such as stochastic actor-oriented models (SAOM) can be used to study the dynamics of network formation.

Fourth, owing to the unavailability of any other relational data source about firms, the relational data was collected from firms' managers. This is a crucial limitation of this study because there is a possibility that some managers may be more socially embedded in their contacts than others, and therefore their advice-seeking behaviour may differ from others, which in turn could misrepresent the firm-level collaboration activities. However, the focus of this research is to investigate innovation-related interactions, and the literature acknowledges that knowledge workers (managers) are often the key source of knowledge and ideas in firms (Huber, 2013). This issue could be resolved by asking multiple managers about their advice sharing activities to map a single large network.

The fifth limitation is that the thesis only focuses on product and process innovation linkages to mapping networks, and does not analyse other types of potential linkages that commonly exist among collaborating firms in clusters as business linkages, technical linkages, marketing linkages etc. Moreover, since the focus of this study is on innovation types so the study could also have analysed incremental, radical, organisational and marketing innovation linkages among firms. A related limitation of this study is that it captures product and process linkages based on informal advice relationships among firms' managers.

The sixth limitation is related to the estimation modelling. For instance, the literature on proximity dimensions argue that these dimensions can have an inverted U-shaped relationship with innovation (Boschma, 2005); however, I did not test this relationship. The reason being that the main purpose of this study is to investigate the distinct impact of proximity dimensions on the formation of product and process innovation networks. Therefore, I did test the inverted U-shaped relationship between proximity dimensions and innovation networks. Further, research can extend this study to investigate the proximity paradox (Broekel and Boschma, 2012) and the Goldilocks principle (Fitjar et al., 2016) to test the inverted U-shaped relation among product and process innovation networks and proximity dimensions.

The final limitation is regarding the operationalisation of key variables. In the third paper, I measure the dependent variable, which is innovation performance, by counting the number of international certifications obtained by each firm. This measure is used based on the suggestion of local managers because the cluster firms are not involved in radical innovations, and each firm believes that it improves/innovates products and processes regularly. Therefore, it was difficult to separate innovative with non-innovative firms. Future research should use more direct measures of innovative performance, such as the percentage of innovative sales in the total amount of sales. Although innovation performance is crucial, future studies can extend this research by investigating different measures of performance, such as export performance and economic performance. Moreover, the operationalisation of strong and weak ties is not based on typical measures used in network research. I consider a relationship to be strong when two firms share both product and process-related knowledge and assume ties as weak when two firms share a single type of knowledge. Future research should ask direct questions on the strength of ties. Another limitation of this research is the small sample size. Particularly for the third paper in this study, a sample size of 73 firms is an important limitation because this paper employed standard OLS regression, which may demand a large sample size. While sample size may be a limitation for the third papers, it is not a problem for the first and second paper of the thesis because in relational and network studies the unit of analysis is linked among actors; therefore sample size does not create any issue.

6.5 Final words

To conclude, this thesis has revealed that cluster firms are embedded in multiple kinds of innovation networks. The first two chapters of the thesis provide empirical evidence that the antecedents and drivers of product and process innovation networks differ from each other. In the first empirical chapter, I have shown that the importance of various proximity dimension differs across product and process innovation networks. While spatial proximity is relatively more important for product innovations networks, non-spatial proximities have demonstrated a relatively higher impact on the formation of process innovations networks. The second chapter has further established that firms' capabilities, business relationships and endogenous network effects also play a distinct role in the formation and dynamics of product and process innovation networks. In addition to the contribution to the debate on multiple networks, this thesis has contributed to the debate on the importance of prominent network position in a network of asymmetric relations. The third empirical chapter provides evidence that the innovation performance of firms depends on their position in the network of asymmetric relations. The results revealed that a prominent role in the advice-giving network positively influence firms' innovation performance, whereas a prominent position in the advice sharing has a significant negative impact on the performance of firms. Furthermore, the paper found that firms' capabilities play a crucial role in mediating the impact of structural embeddedness on innovation.

Although this thesis made several contributions to the extant literature on innovation networks, there are still interesting questions that future research can explore. For instance, future studies may extend this research by investigating other types of innovation-related interactions and examine the formation and dynamics of different types of innovation networks. In this respect, an interesting question would be to investigate how different dimensions of proximity, firms' attributes and endogenous network properties influence the knowledge spillovers in the exploratory and exploitative innovations, or radical and incremental innovations, or services and product innovations. It would also be interesting to study the evolution of multiplex networks by collecting network data over time. Finally, this research may be extended to examine the impact of firms' structural and relational embeddedness in different types of relations on the innovation outcome of firms.

Innovation networks is a growing research area. While scholars have widely acknowledged the importance of networks, the research on multiple networks remains scarce. This thesis has attempted to contribute to our understanding of the formation and consequences of innovation networks. However, there are several areas which require the attention of network scholars and much more is needed to understand the dynamics of networks. It is thus anticipated that the contributions of this thesis to the literature on innovation networks open new stimulating questions for future research to answer.

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Appendices

APPENDIX-A

Absorptive Capacity Measure

Absorptive capacity has been measured by applying Principal Component Analysis to the following two correlated variables.

A1. Variable 1: Local and Foreign Human Resources

This variable provides the background of each firm's skilled labour force that can play a significant role in the introduction of product and process innovations. According to previous studies, higher education level of an employee significantly contributes to innovation process. I identified the skilled human resource in both marketing and production departments because it is often argued that costumers are more important for product innovations and suppliers are more important for process innovations. In our research context, marketing managers (business graduates) interact with costumers and production/R&D managers (engineers) interact with suppliers, therefore I focused on both the business graduates and engineers. Additionally, I sought information about further master degree in engineering (this was not perceived as very important, however still a plus point for employers), employees with foreign degree holders are also a plus point. Employees with foreign experiences are very important. I were informed during the interviews that, in the local textile cluster foreign experience is a plus point especially in value added products manufacturing. I calculated the variable as follows;

Human resource = (MBA degree holders x 0.3) + (BSc engineering degree holders x 0.3) + (Master degree x 0.05) + (Foreign degree x 0.15) + (Foreign experience x 0.2)

A2. Variable 2: Research Efforts

The second variable was calculated using a 3-point score system. Three important research effort/ activities were chosen on the guidance of literature and each was allocated either a 1/0 score. For instance, firms with a dedicated

R&D department was given 1 point and firms without a dedicated R&D department was given a 0 score. The three activities/ research efforts are;

1. Separate dedicated R&D department (x1)
2. Part of a larger business group (x2)
3. Involved in Joint R&D projects with customers/suppliers/universities etc. (x3)

Research Efforts = x1 + x2 +x3

Firms involved in all the three research activities received 3 points and firms with involvement in none of the activities received 0 points. Importance of a separate R&D department has been highlighted by several scholars (e.g. Cohen and Levintha 1990). Belonging to a group of firms provide access to large pool of resources and state-of-the-art knowledge available with the business group (Kim and Lui 2015). I asked the firms if they had conducted joint research projects with universities, customers, suppliers or other external partner in last two years.

A3. Variable 3: Internationalisation Efforts

The third variable was calculated using a 2-point score system. Two important internationalisation activities were chosen on the guidance of literature and each was allocated either a 1/0 score. For instance, firms with a dedicated international sales department was given 1 point and firms without a dedicated international office was given a 0 score. The two internationalisation activities and efforts are;

1. Separate International Liaison Office (s) in Global Market (y1)
2. Hire special Foreign Consultants for Product/Process Improvement (y2)

Internationalisation Efforts = y1 + y2

Firms involved in both the internationalisation activities received 2 points and firms with involvement in none of the activities received 0 points. Importance of international office was highlighted by the local managers and almost all leading firms have had at least one international liaison office. Finally, I observed during the pilot study that leading firms often hire foreign consultants from Germany, Italy, Turkey, Japan, Singapore, and Sri Lanka etc. for the development of both products and process innovations. Therefore, I decided to add this as a part of second variable.

Principal Component Analysis extracted one component, which was used as a measure for absorptive capacity in our study. The PCA explained 69% of the variation.

Principal Component Analysis

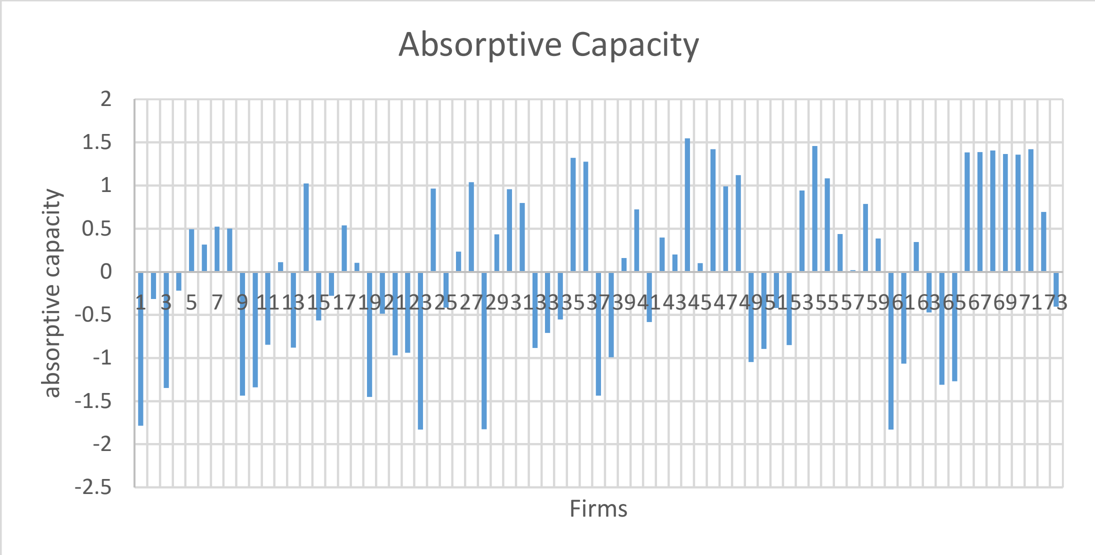
Correlation Matrix

		Std. Deviation	1	2	3
1	Research Efforts	0.91	1		
2	Human Resource	0.34	0.49***	1	
3	Internationalisation Efforts	0.83	0.59***	0.52***	1

	Extraction
Research Efforts	.705
Human Resource	.642
Internationalisation Efforts	.730

Total Variance Explained

		Initial Eigenvalues		
		Total	% of Variance	Extracted % of Variance
1	Research Efforts	2.077	69.234	69.234
2	Human Resource	0.521	17.367	
3	Internationalisation Efforts	0.402	13.399	



Firms	PCA Factor values
1	-1.80441
2	-0.32025
3	-0.87053
4	-0.22849
5	0.48266
6	0.31061
7	0.52187
8	0.49384
9	-1.4606
10	-1.35737
11	-0.86445
12	0.10414
13	-0.89347
14	1.02685
15	-0.5726
16	-0.29123
17	0.53334
18	0.09238
19	-1.47207
20	-0.49769
21	-0.99062
22	-0.95621
23	-1.8503
24	0.96412
25	-0.42349
26	0.22394
27	1.03803
28	-1.8503
29	0.4304
30	0.95803
31	0.79206
32	-0.89856
33	-0.7268
34	-0.56622
35	1.32478
36	1.2789
37	-1.4606
38	-1.01356
39	0.14973
40	0.71686
41	-0.59554
42	0.39569
43	0.19561
44	1.55419
45	0.09238
46	1.42802
47	0.99215
48	1.11832
49	-1.05944
50	-0.91033
51	-0.42319
52	-0.86445
53	0.9348
54	1.46243
55	1.08391
56	0.4314
57	0.007
58	0.78059
59	0.37913
60	-1.8503
61	-1.08208
62	0.33864
63	-0.48084
64	-1.32296
65	-1.28855
66	1.38851
67	1.3936
68	1.40507
69	1.35919
70	1.35919
71	1.42802
72	0.68883
73	-0.41172

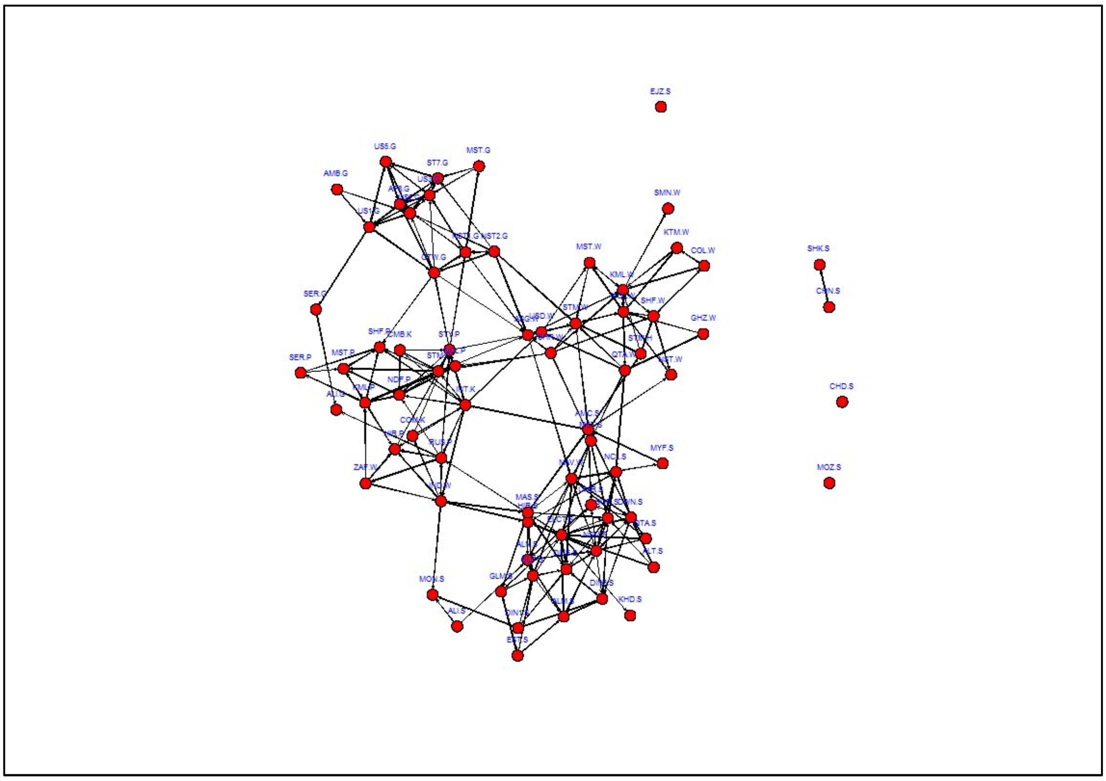


Figure 4-1 Process Innovation Network (Observed)

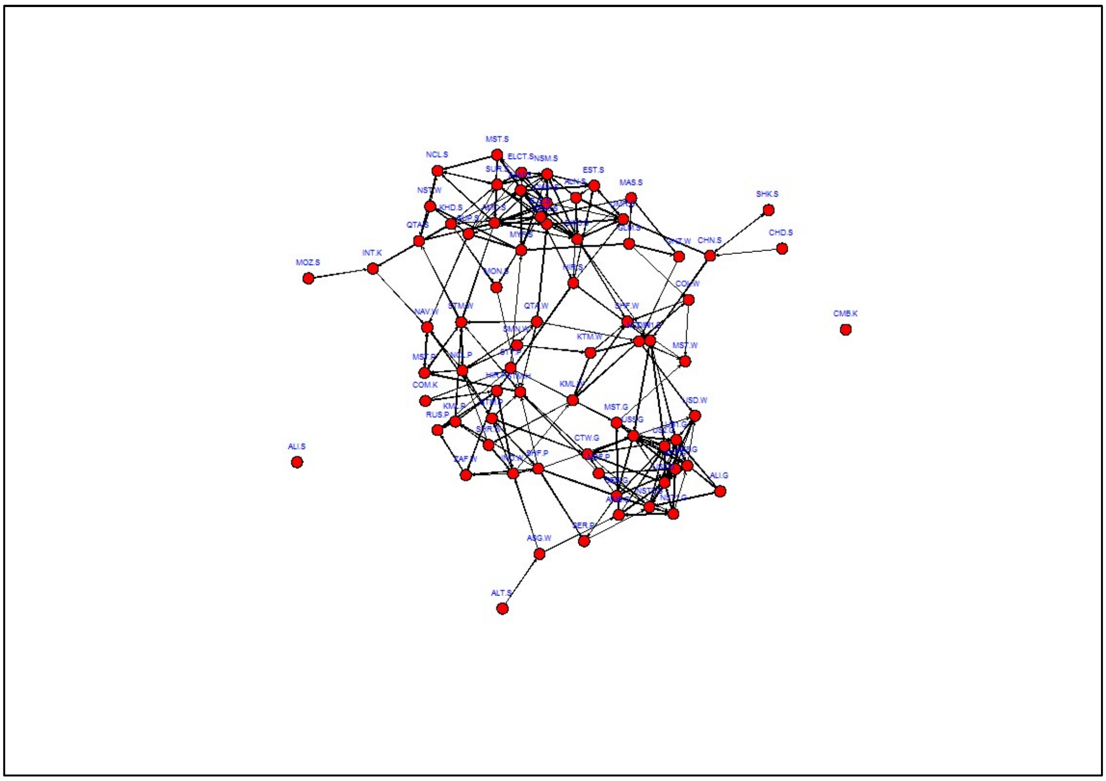


Figure 4-2 Process Innovation Network (Simulated with 200 simulations)

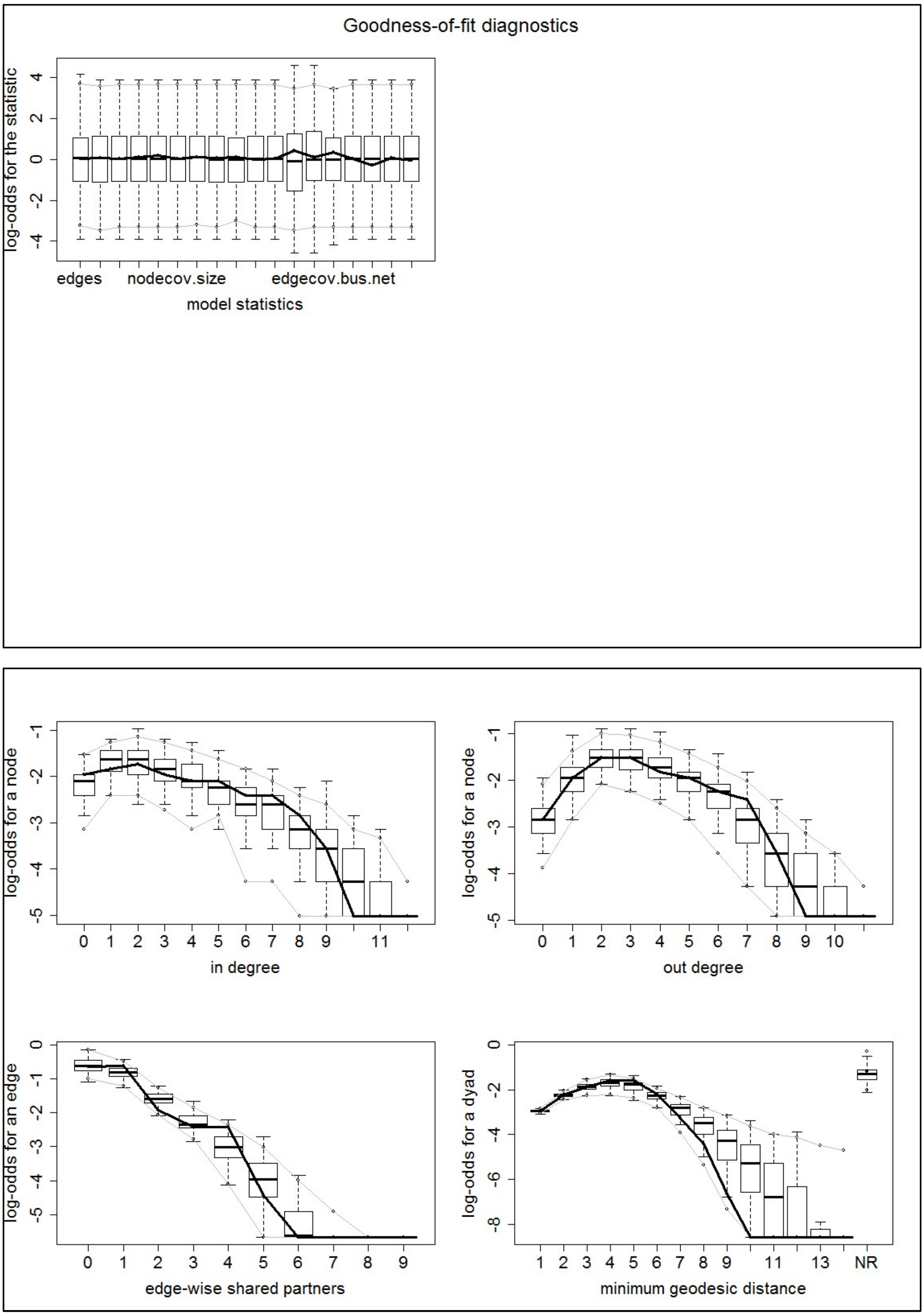
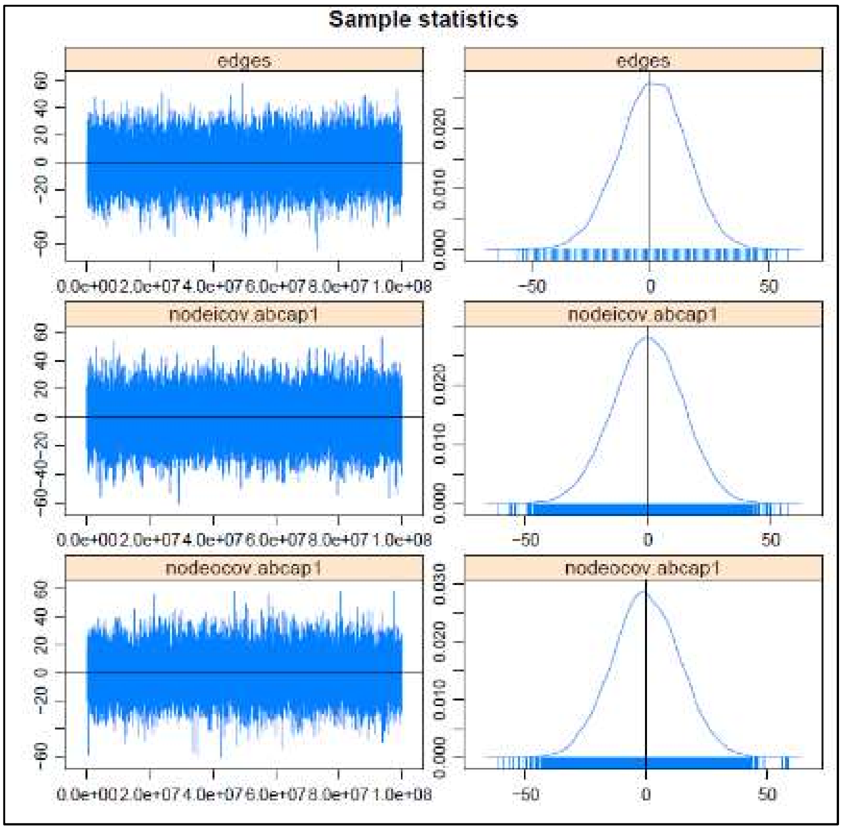
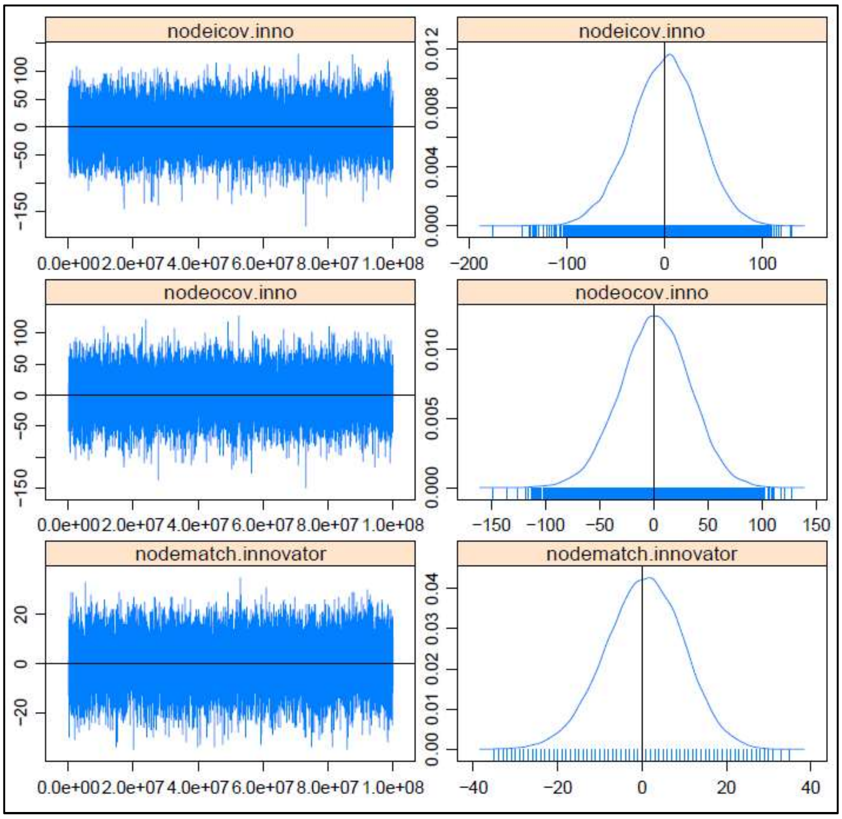


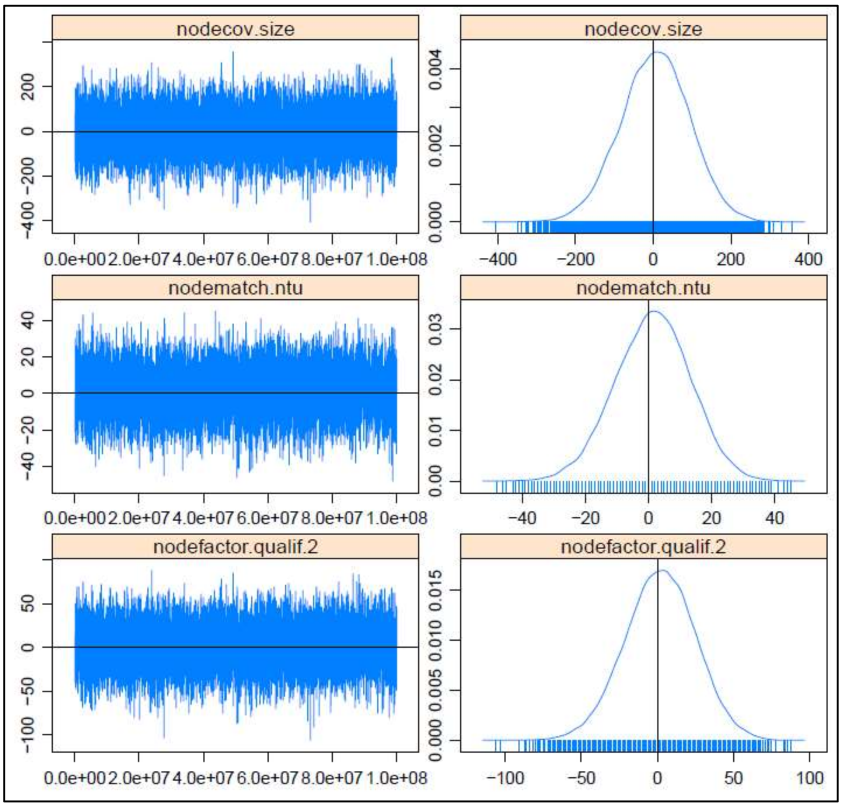
Figure 4-3 Goodness of fit statistics - Process Innovation network


Sample statistics
edges
edges
nodeicov.abcap1
nodeicov.abcap1
nodeocov.abcap1
nodeocov.abcap1

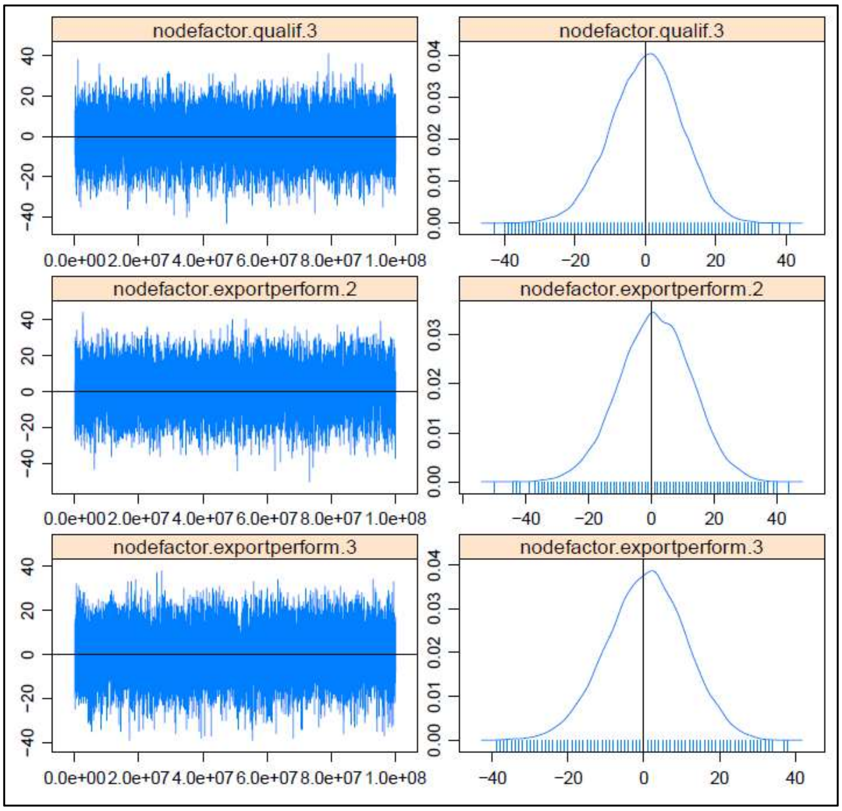
(a)


nodeicov.inno
nodeicov.inno
nodeocov.inno
nodeocov.inno
nodematch.innovator
nodematch.innovator

(b)


nodecov.size
nodematch.ntu
nodefactor.qualif.2

(c)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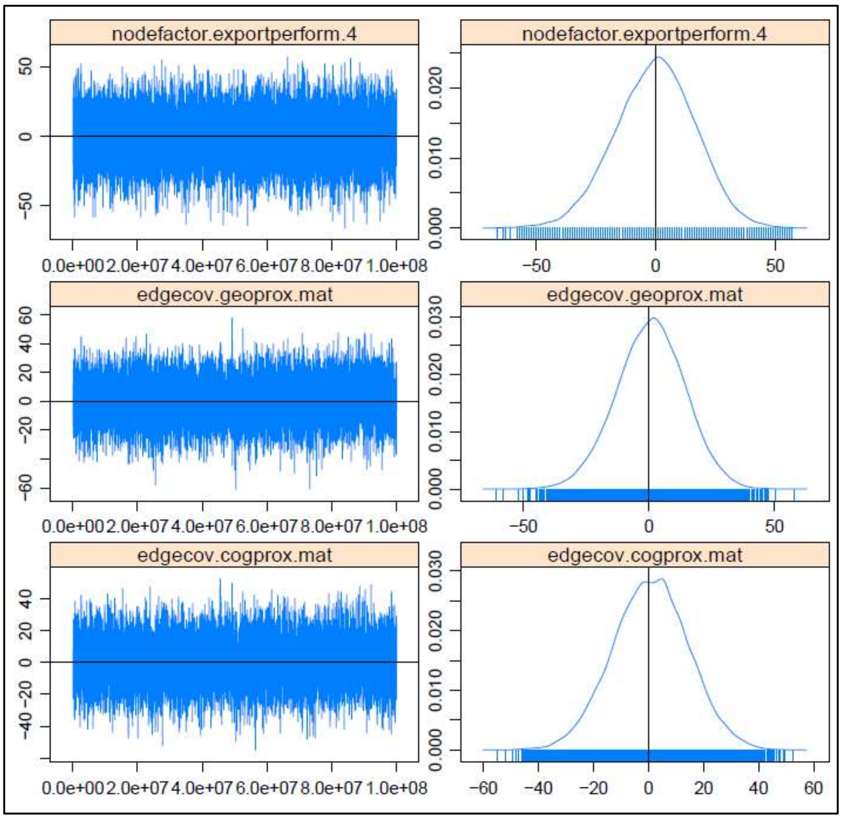
nodefactor.exportperform.2
nodefactor.exportperform.3

(d)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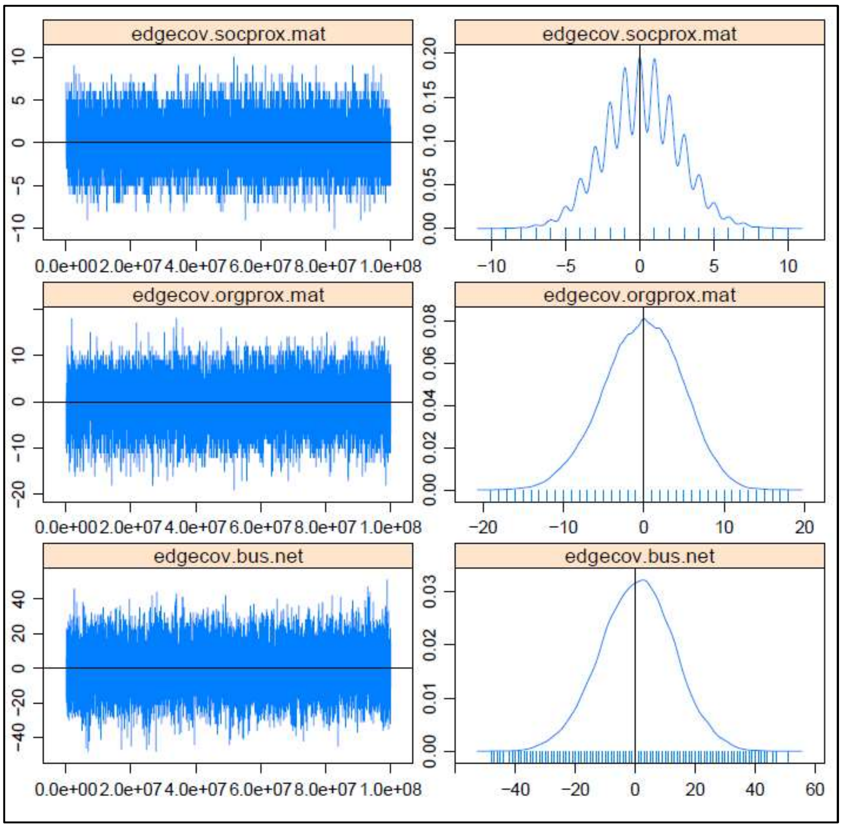
edgecov.geoprox.mat
edgecov.cogprox.mat

(e)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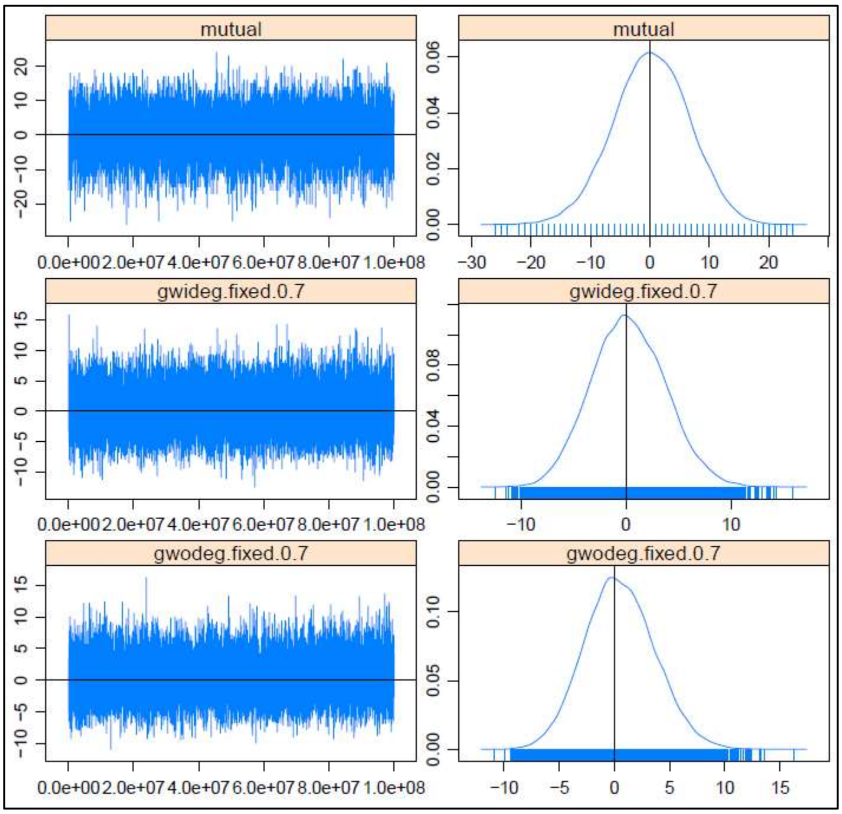
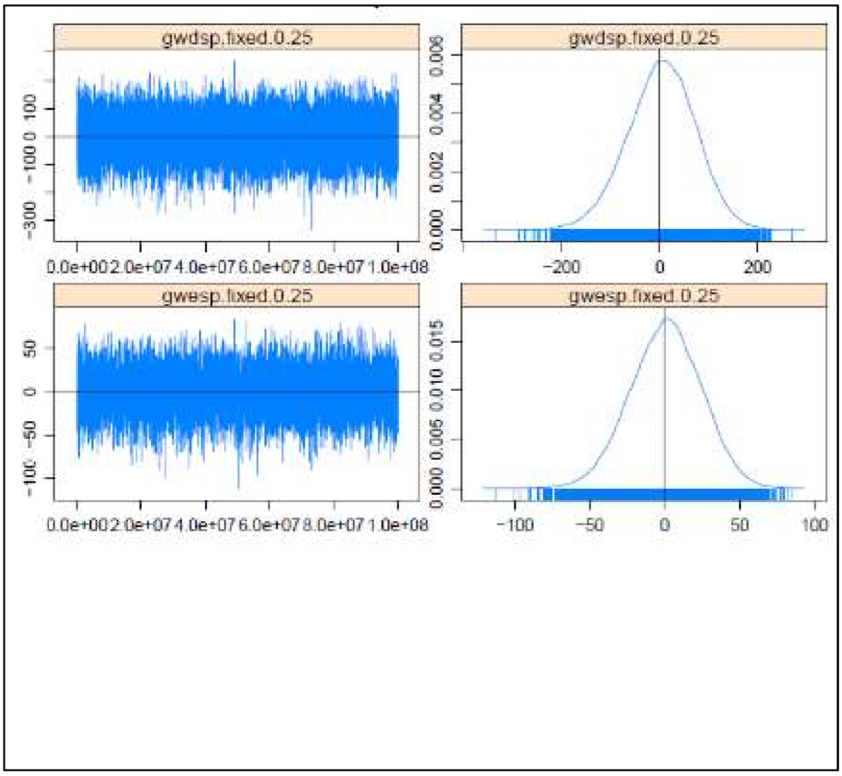
edgecov.orgprox.mat
edgecov.bus.net

(f)



(g)



(h)

Figure 4-4 (a-h) Robustness check for Process Innovation Network (MCMC diagnostics)

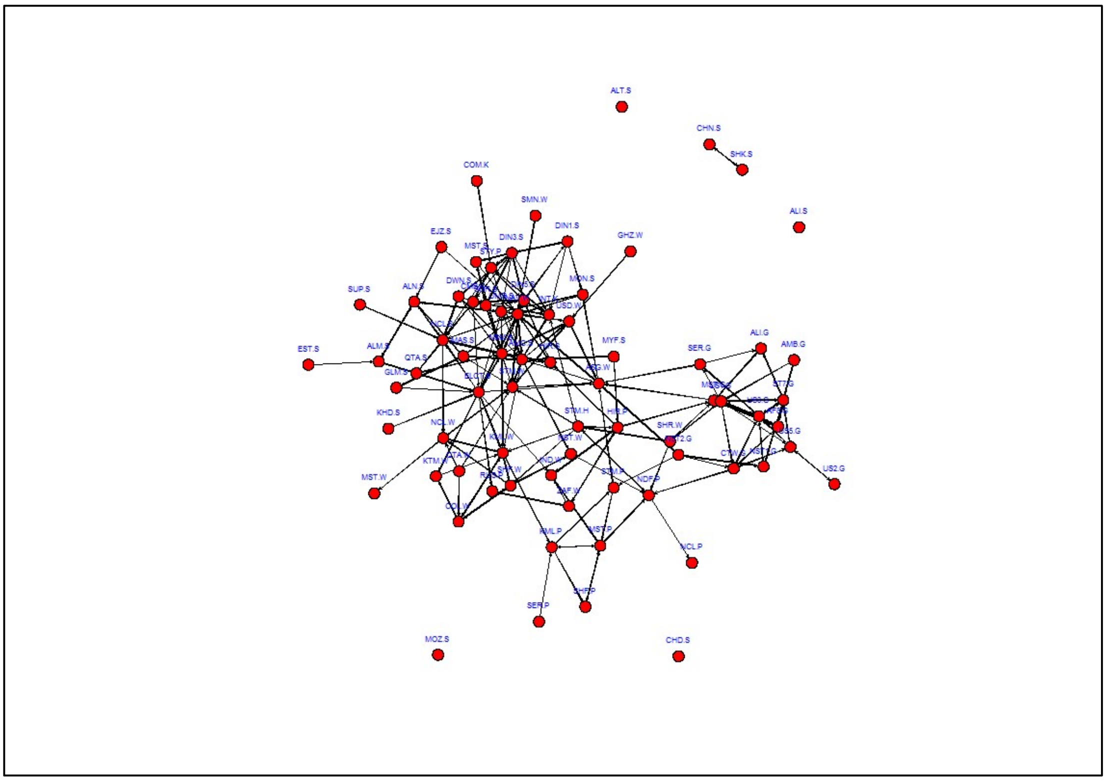


Figure 4-5 Product Innovation Network (Observed)

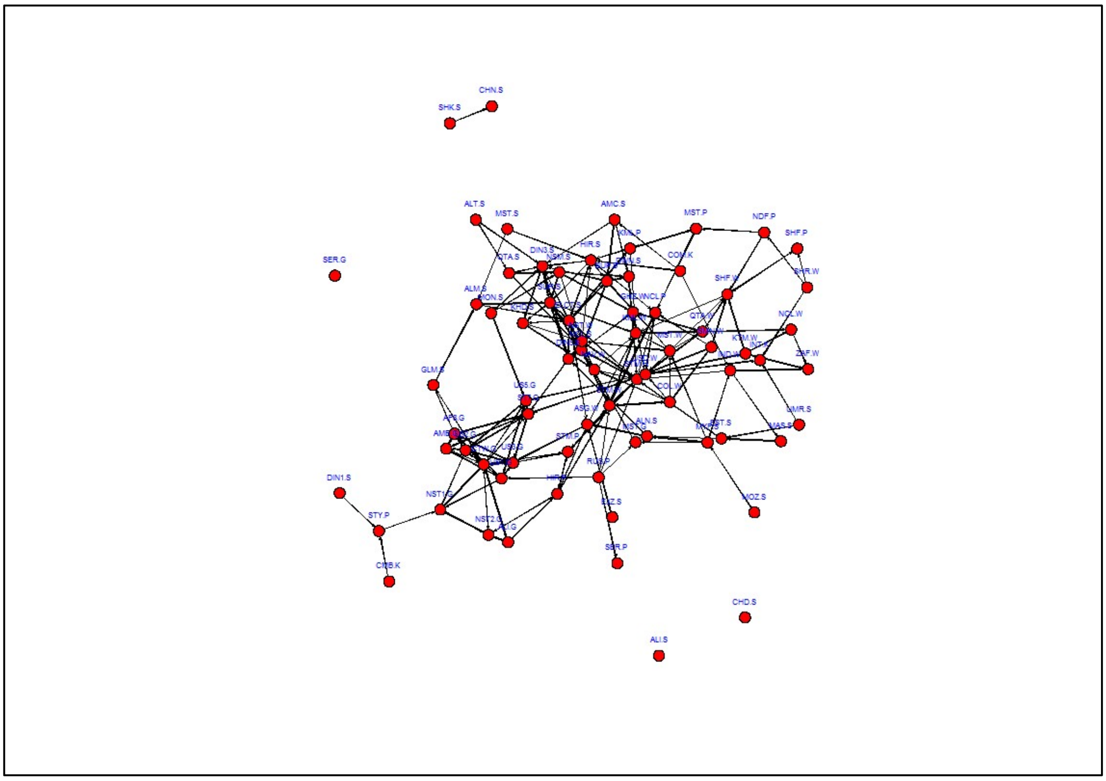
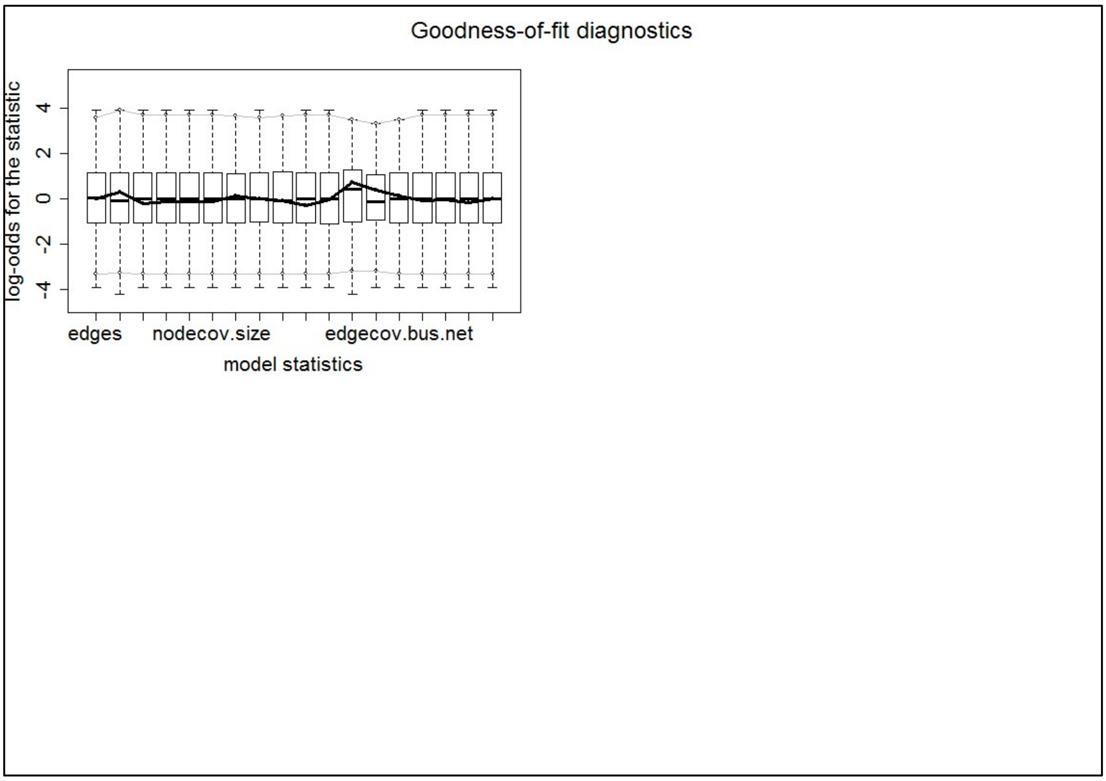


Figure 4-6 Product Innovation Network (Simulated 200 simulations)



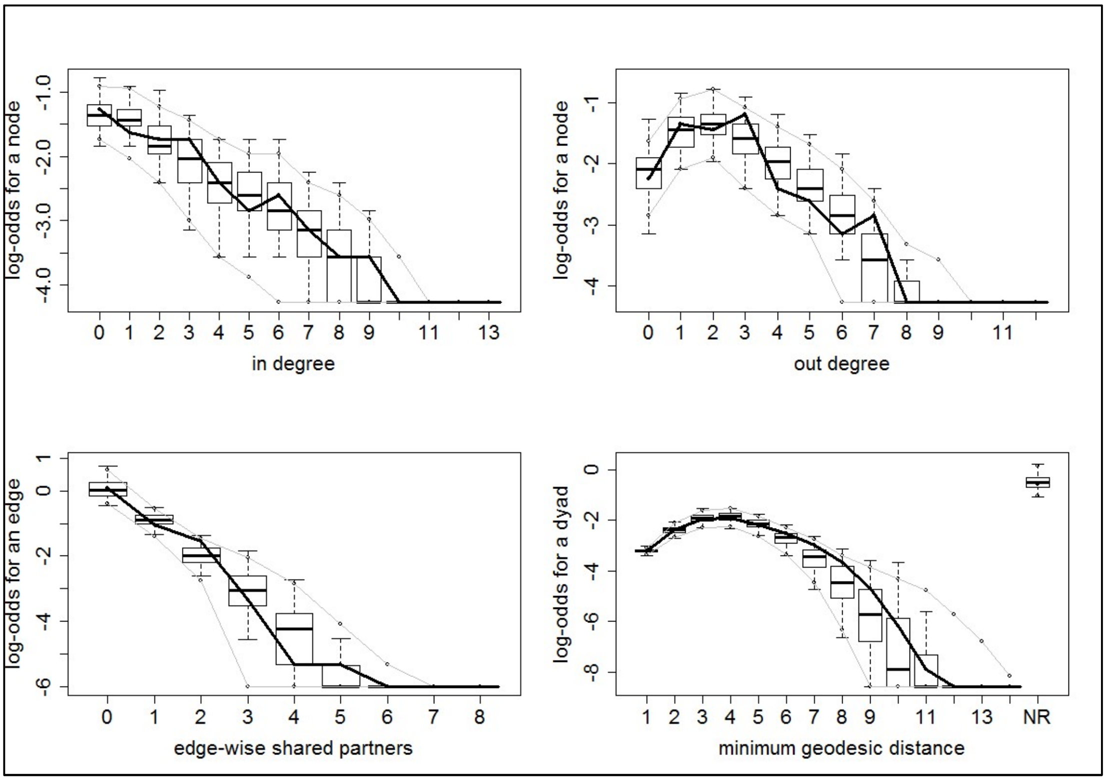
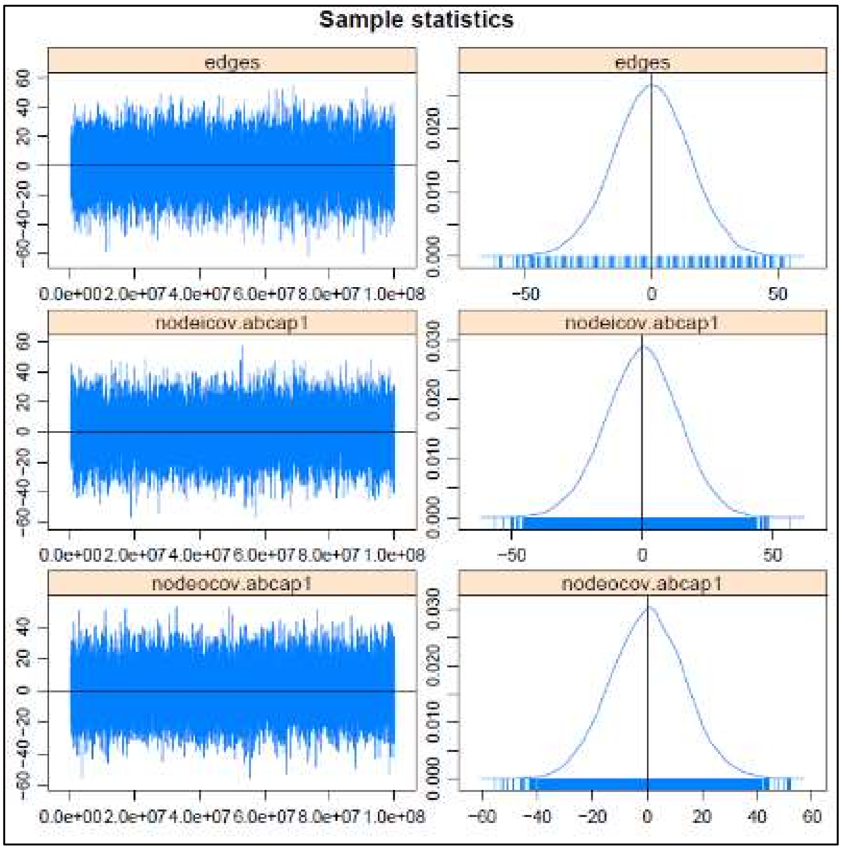
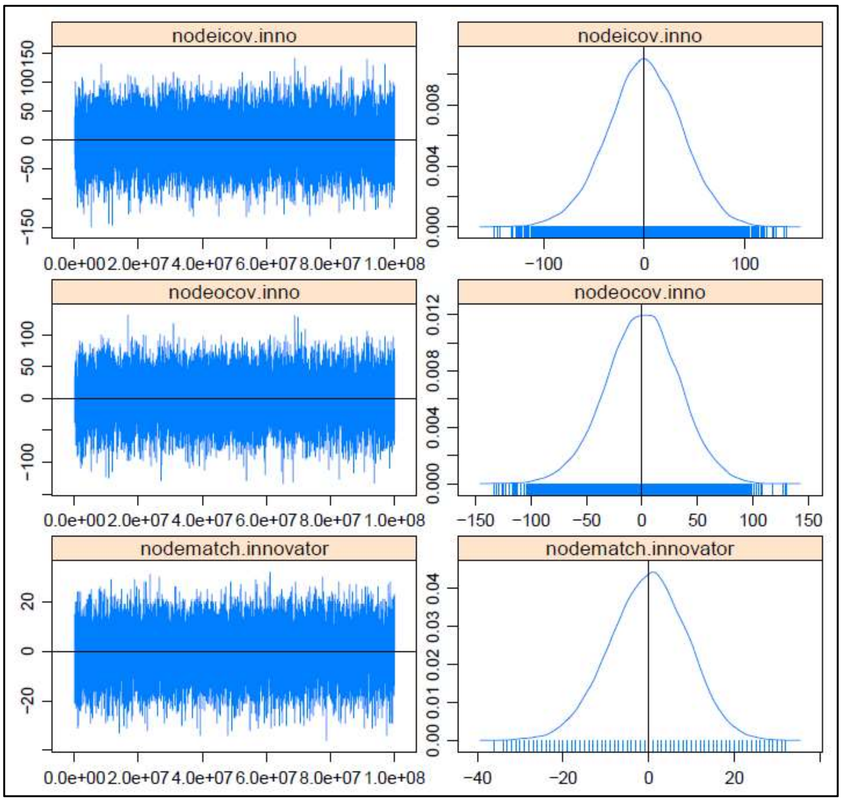


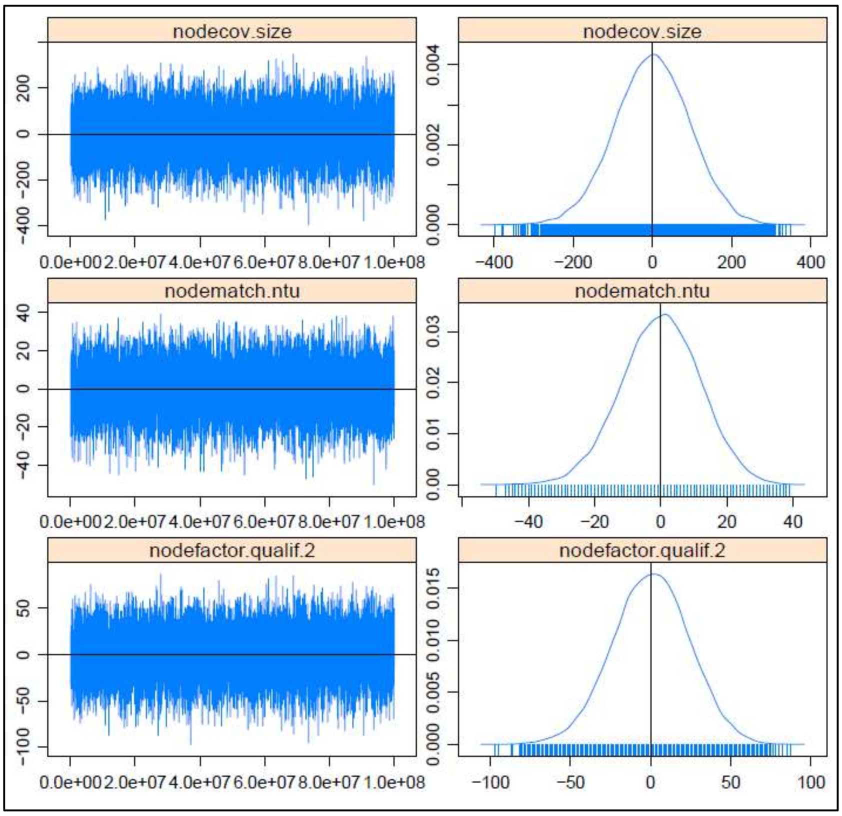
Figure 4-7 Goodness of fit statistics for Product Innovation Network


Sample statistics
edges
nodeicov.abcap1
nodeocov.abcap1

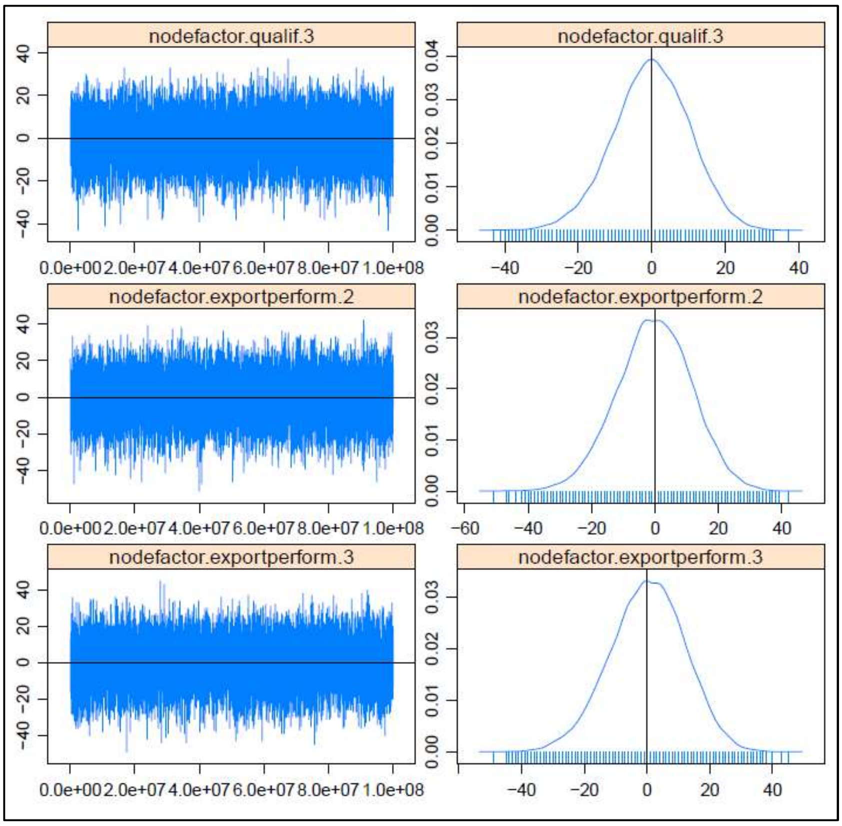
(a)


nodeicov.inno
nodeocov.inno
nodematch.innovator

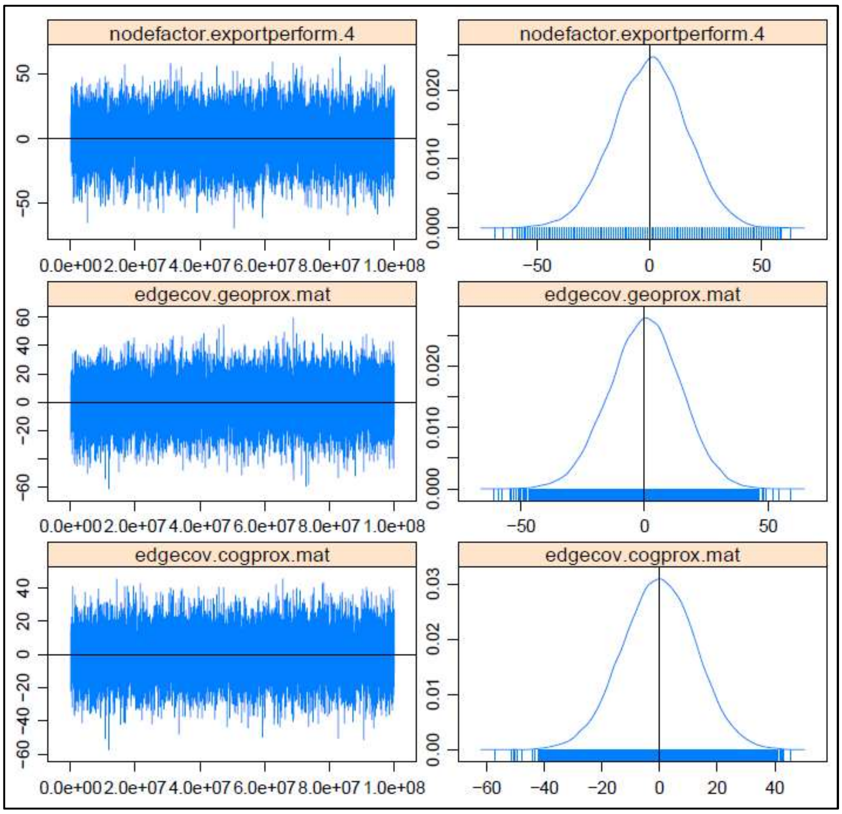
(b)


nodecov.size
nodecov.size
nodematch.ntu
nodematch.ntu
nodefactor.qualif.2
nodefactor.qualif.2
0.0e+00 2.0e+07 4.0e+07 6.0e+07 8.0e+07 1.0e+08

(c)

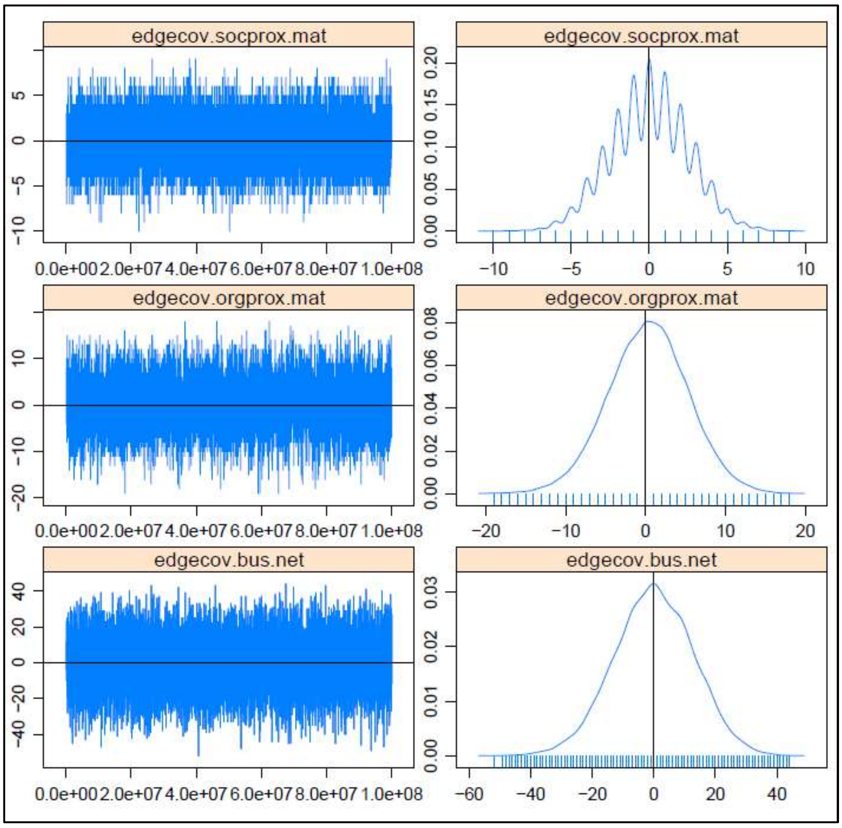

nodefactor.qualif.3
nodefactor.qualif.3
nodefactor.exportperform.2
nodefactor.exportperform.2
nodefactor.exportperform.3
nodefactor.exportperform.3
0.0e+00 2.0e+07 4.0e+07 6.0e+07 8.0e+07 1.0e+08

(d)



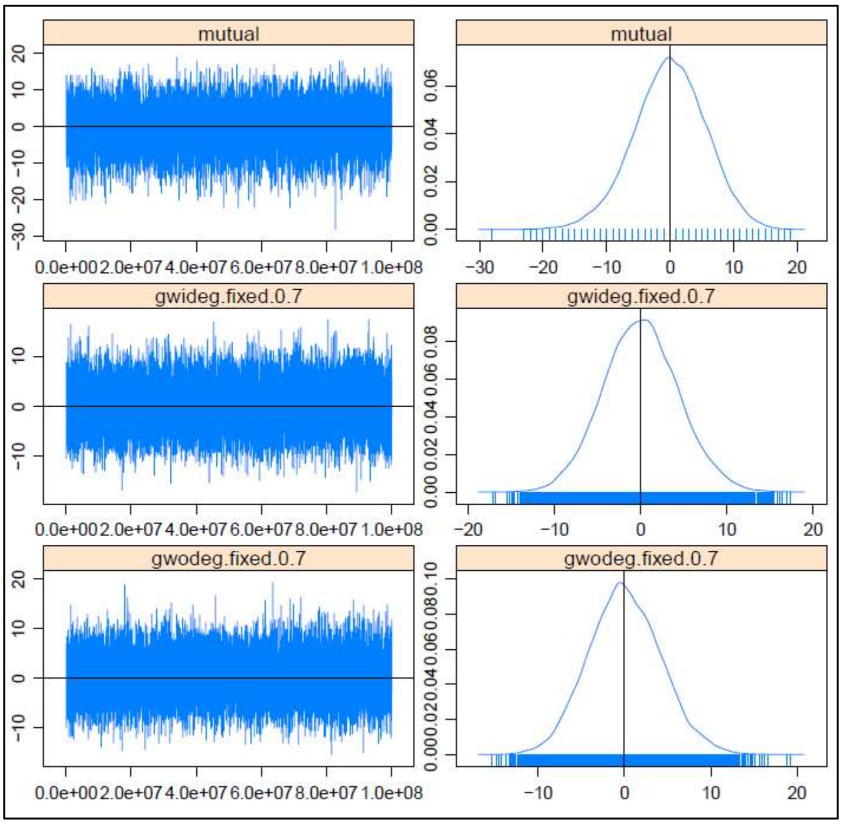
nodefactor.exportperform.4
nodefactor.exportperform.4
edgecov.geoprox.mat
edgecov.geoprox.mat
edgecov.cogprox.mat
edgecov.cogprox.mat

(e)

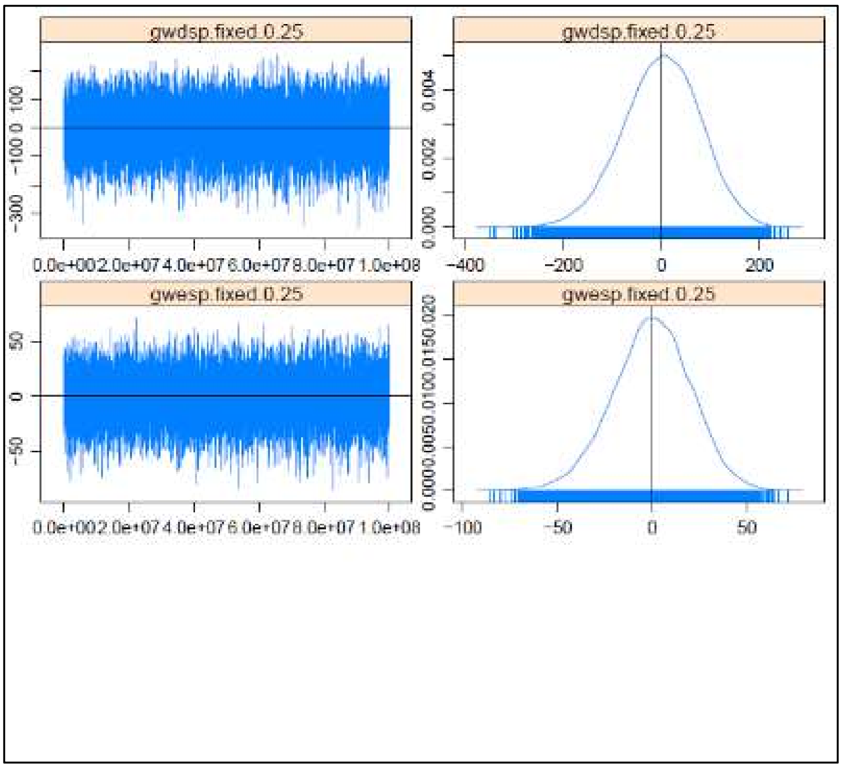


edgecov.socprox.mat
edgecov.socprox.mat
edgecov.orgprox.mat
edgecov.orgprox.mat
edgecov.bus.net
edgecov.bus.net

(f)



(g)



(h)

Figure 4-8 (a-h) Robustness check for Product Innovation Network (MCMC diagnostics)

Appendix C

Questionnaire:

Confidentiality statement. I regard the information that you provide on this questionnaire as highly confidential. After the data is made anonymous with respect to respondent, the original questionnaires will be destroyed to preserve privacy.

A GENERAL INFORMATION/ Firm-level Characteristics

1. Name of firm
2. Address
3. Telephone & E-mail
4. Name of interviewee
5. Role within the firm
6. Qualification
7. Total job experience (years)
8. Experience in the current firm (years).
9. Year of establishment of the firm
10. Production Capacity Installed ______________________
11. Number of total permanent employees in the firm (number).
12. Exports percentage

ABSORPTIVE CAPACITY/ KNOWLEDGE BASE:

13. What %age of employees are involved in marketing/sales operations (%age).
14. What %age of employees are responsible for technical operations (%age).
15. What %age of technical employees have university level qualification (%age).
    a. Technical Diploma
    b. B.E / MSc (16 years)
    c. MS/MPhil (17/18 years)
    d. Doctorate
16. What %age of technical employees are foreign degree holders.
17. What %age of technical employees have work experience in foreign countries?
18. Employees working in R&D and/or PD department, or responsible for the R&D (%age).
19. Budget of R&D and PD department (%age of total sales)

NEW PRODUCT & PROCESS DEVELOPMENT:

20. Are you involved in the development of new products or product innovation?
    a. Yes/No
21. Please identify which of the following source of knowledge is more helpful in the development of new products or product innovation.
    a. Customers/ Buyers - *downstream*
    b. Suppliers of equipment/machinery – *upstream*
    c. Suppliers of raw material (e.g. chemical, fabric, yarn, fibre, lycra etc) - *upstream*
    d. Supplier of intermediately product (input material) - *upstream*
    e. Competitors - *horizontal*
    f. Consulting firms
    g. Academia/ R&D Institutes

22. How often you contact the below source of knowledge? Please encircle your choice in brackets.
    a. Customers/ Buyers - *downstream*
    b. Suppliers of equipment/machinery – *upstream*
    c. Suppliers of raw material (e.g. chemical, fabric, yarn, fibre, lycra etc) - *upstream*
    d. Supplier of intermediately product (input material) - *upstream*
    e. Competitors - *horizontal*
    f. Consulting firms
    g. Academia/ R&D Institutes
23. Are you involved in the development of new processes or process innovation?
    a. Yes/No
24. Please identify which of the following source of knowledge is more helpful in the development of new processes or process innovation.
    a. Customers/ Buyers - *downstream*
    b. Suppliers of equipment/machinery – *upstream*
    c. Suppliers of raw material (e.g. chemical, fabric, yarn, fibre, lycra etc) - *upstream*
    d. Supplier of intermediately product (input material) - *upstream*
    e. Competitors - *horizontal*
    f. Consulting firms
    g. Academia/ R&D Institutes
25. How often you contact the below source of knowledge? Please encircle your choice in brackets.
    a. Customers/ Buyers - *downstream*
    b. Suppliers of equipment/machinery – *upstream*
    c. Suppliers of raw material (e.g. chemical, fabric, yarn, fibre, lycra etc) - *upstream*
    d. Supplier of intermediately product (input material) - *upstream*
    e. Competitors - *horizontal*
    f. Consulting firms
    g. Academia/ R&D Institutes
26. Can you please name five firms who do you think are leaders in product innovation?
    a. ________________________________
    b. ________________________________
    c. ________________________________
    d. ________________________________
    e. ________________________________
27. Can you please name five firms who do you think are leaders in process innovation?
    a. ________________________________
    b. ________________________________
    c. ________________________________
    d. ________________________________
    e. ________________________________

PROXIMITY VARIABLES

- Institutional Proximity (This will be excluded from the next fieldwork)

Is your firm registered with the Pakistan Stock Exchange Market?

1. Yes

2. No

- <u>Organizational Proximity</u>

Type of firm

1. Independent Unit

2. Owned by any Group of Companies (Please specify___________________

- <u>Cognitive Proximity</u>

Type of Industry Activity

Spinning (1311)

Weaving (1312)

Textile Processing (1313)

Knitting (1391)

Home Textile Made-ups (1392)

Embroidery work (1399)

Apparel & Garments excl. Knitted (1410)

Knitted Apparel & Garments (1430)

Can you please specify the make and model of your plant's major production machinery/equipment?

1. Make of Production Equipment (Manufacturer name _______________)
2. Model of Production Equipment (Year of Manufacture_________________)

- <u>Social Proximity</u>

From which university and College have you been graduated?

1. Please specify your graduation university's name ___________________
2. Please specify college name _____________________

Please provide name of your last three employers.

1. ____________________________
2. ____________________________
3. ____________________________

Who is the owner of this firm? Can you please specify the clan/tribe of the owner as well?

1. Full Name of Owner _______________
2. Clan/Tribe of the owner _________________

<u>C. PRODUCT & PROCESS INNOVATION KNOWLEDGE NETWORK</u>

- **PRODUCT INNOVATION KNOWLEDGE LINKAGES**

e) **When you need technical advice on product development/innovation, to which of the local firms mentioned in the roster do you turn?** (list with all names of the firms in the cluster will be provided) [Please rate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high].

f) **Which of the firms in the roster do you think have benefited from technical support for product development/innovation from this firm? (**list with all names of the firms in the cluster will be provided) [Please indicate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high].

Product Innovation Roster (Sample-original names removed)

Sr. No	Name of Firms	Location	Column # 1 Product Issues	Column # 2 Usefulness/ Importance
0	**Example**	**Example**	**X**	**5**
1	Firm 1	Manga-Lahore		
2	Firm 2	Manga-Lahore		
3	Firm 3	Defence Rd-Lahore		
4	Firm 4	Manga-Lahore		
5	Firm 5	GlaxoTown-Lahore		
6	Firm 6	Rohi Nala-Lahore		
7	Firm 7	Bhaiperu-Lahore		
8	Firm 8	Manga-Lahore		
9	Firm 9	Manga-Lahore		
10	Firm 10	Bhaiperu-Lahore		
11	Firm 11	Manga-Lahore		
12	Firm 12	Sundar-Lahore		
13	Firm 13	Kot Lakhpat-Lahore		
14	Firm 14	Atari Road-Lahore		
15	Firm 15	Bhaiperu-Lahore		
16	Firm 16	Bhaiperu-Lahore		
17	Firm 17	Raiwind-Lahore		
18	Firm 18	Raiwind-Lahore		
19	Firm 19	Bhaiperu-Lahore		
20	Firm 20	Manga-Lahore		
21	Firm 21	Manga-Lahore		
22	Firm 22	Bhaiperu-Lahore		
23	Firm 23	Manga-Lahore		
24	Firm 24	Manga-Lahore		
25	Firm 25	Manga-Lahore		
26	Firm 26	Manga-Lahore		
27	Firm 27	Manga-Lahore		
28	Firm 28	Manga-Lahore		
29	Firm 29	Manga-Lahore		
30	Firm 30	Manga-Lahore		
31	Firm 31	Manga-Lahore		
32	Firm 32	Raiwind-Lahore		
33	Firm 33	Raiwind-Lahore		
34	Firm 34	Raiwind-Lahore		
35	Firm 35	Raiwind-Lahore		
36	Firm 36	Manga-Lahore		
37	Firm 37	Raiwind-Lahore		
38	Firm 38	Defense Rd-Lahore		
39	Firm 39	Defense Rd-Lahore		

40	Firm 40	Raiwind-Lahore	x	4
41	Firm 41	Bhaiperu-Lahore	x	4
42	Firm 42	Bhaiperu-Lahore		
43	Firm 43	Manga-Lahore		
44	Firm 44	Rohi Nala-Lahore		
45	Firm 45	Rohi Nala-Lahore		
46	Firm 46	Rohi Nala-Lahore		
47	Firm 47	Rohi Nala-Lahore		
48	Firm 48	Rohi Nala-Lahore		
49	Firm 49	Bhaiperu-Lahore		
50	Firm 50	Bhaiperu-Lahore		
51	Firm 51	Rohi Nala-Lahore		
52	Firm 52	Manga-Lahore		
53	Firm 53	Manga-Lahore		
54	Firm 54	Manga-Lahore		
55	Firm 55	Defence Rd-Lahore		
56	Firm 56	Rohi Nala-Lahore		
57	Firm 57	Lahore-Sargoda Rd		
58	Firm 58	Manga-Lahore		
59	Firm 59	Manga-Lahore		
60	Firm 60	Kot Lakhpat-Lahore		
61	Firm 61	Bhaiperu-Lahore		
62	Firm 62	Kot Lakhpat-Lahore		
63	Firm 63	Raiwind-Lahore		
64	Firm 64	Manga-Lahore		
65	Firm 65	Raiwind-Lahore		
66	Firm 66	Defense Rd-Lahore		
67	Firm 67	Ferozpur Rd-Lahore		
68	Firm 68	Defense Rd-Lahore		
69	Firm 69	GlaxoTown-Lahore		
70	Firm 70	Defense Rd-Lahore		
71	Firm 71	Glaxo Town-Lahore		
72	Firm 72	Glaxo Town-Lahore		
73	Firm 73	Bhaiperu-Lahore		
Please mention other Firms from Lahore Only				
76				
77				
78				
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- **PROCESS INNOVATION LINKAGES**

g) **When you need technical advice on process improvement/innovation, to which of the local firms mentioned in the roster do you turn?** (list with all names of the firms in the cluster will be provided) [Please rate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high].

h) **Which of the firms in the roster do you think have benefited from technical support for process improvement/innovation from this firm? (**list with all names of the firms in the cluster will be provided) [Please indicate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high].

Process Innovation Roster (sample- original names removed)

Sr. No	Name of Firms	Location	Column # 1 Process Issues	Column # 2 Usefulness/ Importance
0	**Example**	**Example**	**X**	**5**
1	Firm 1	Manga-Lahore		
2	Firm 2	Manga-Lahore		
3	Firm 3	Defence Rd-Lahore		
4	Firm 4	Manga-Lahore		
5	Firm 5	GlaxoTown-Lahore		
6	Firm 6	Rohi Nala-Lahore		
7	Firm 7	Bhaiperu-Lahore		
8	Firm 8	Manga-Lahore		
9	Firm 9	Manga-Lahore		
10	Firm 10	Bhaiperu-Lahore		
11	Firm 11	Manga-Lahore		
12	Firm 12	Sundar-Lahore		
13	Firm 13	Kot Lakhpat-Lahore		
14	Firm 14	Atari Road-Lahore		
15	Firm 15	Bhaiperu-Lahore		
16	Firm 16	Bhaiperu-Lahore		
17	Firm 17	Raiwind-Lahore		
18	Firm 18	Raiwind-Lahore		
19	Firm 19	Bhaiperu-Lahore		
20	Firm 20	Manga-Lahore		
21	Firm 21	Manga-Lahore		
22	Firm 22	Bhaiperu-Lahore		
23	Firm 23	Manga-Lahore		
24	Firm 24	Manga-Lahore		
25	Firm 25	Manga-Lahore		
26	Firm 26	Manga-Lahore		
27	Firm 27	Manga-Lahore		
28	Firm 28	Manga-Lahore		
29	Firm 29	Manga-Lahore		
30	Firm 30	Manga-Lahore		
31	Firm 31	Manga-Lahore		
32	Firm 32	Raiwind-Lahore		
33	Firm 33	Raiwind-Lahore		
34	Firm 34	Raiwind-Lahore		
35	Firm 35	Raiwind-Lahore		
36	Firm 36	Manga-Lahore		
37	Firm 37	Raiwind-Lahore		
38	Firm 38	Defense Rd-Lahore		
39	Firm 39	Defense Rd-Lahore		
40	Firm 40	Raiwind-Lahore	x	4
41	Firm 41	Bhaiperu-Lahore	x	4
42	Firm 42	Bhaiperu-Lahore		
43	Firm 43	Manga-Lahore		

44	Firm 44	Rohi Nala-Lahore		
45	Firm 45	Rohi Nala-Lahore		
46	Firm 46	Rohi Nala-Lahore		
47	Firm 47	Rohi Nala-Lahore		
48	Firm 48	Rohi Nala-Lahore		
49	Firm 49	Bhaiperu-Lahore		
50	Firm 50	Bhaiperu-Lahore		
51	Firm 51	Rohi Nala-Lahore		
52	Firm 52	Manga-Lahore		
53	Firm 53	Manga-Lahore		
54	Firm 54	Manga-Lahore		
55	Firm 55	Defence Rd-Lahore		
56	Firm 56	Rohi Nala-Lahore		
57	Firm 57	Lahore-Sargoda Rd		
58	Firm 58	Manga-Lahore		
59	Firm 59	Manga-Lahore		
60	Firm 60	Kot Lakhpat-Lahore		
61	Firm 61	Bhaiperu-Lahore		
62	Firm 62	Kot Lakhpat-Lahore		
63	Firm 63	Raiwind-Lahore		
64	Firm 64	Manga-Lahore		
65	Firm 65	Raiwind-Lahore		
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72	Firm 72	Glaxo Town-Lahore		
73	Firm 73	Bhaiperu-Lahore		
Please mention other Firms from Lahore Only				
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